Trade Mark Similarity Assessment Support System

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All praise is due to Allah, the most gracious, the most merciful.

Peace and blessings be upon our Prophet Muhammad

and upon his family and companions.

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To

My Husband, Zulhazmi A. Mokhti

My Children, Faris, Amira & Aisya

My Parents, Hj. Anuar & Hjh. Sabeha

My Late Grandmother, Hjh. Zainah - Al-Fatihah

Declaration and Statements

DECLARATION

This work has not previously been accepted in substance for any degree and is not concurrently submitted in candidature for any degree.

Signed...(candidate) Date ....

Fatahiyah Mohd Anuar

STATEMENT 1

This thesis is being submitted in partial fulfilment of the requirements for the degree of PhD.

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Fatahiyah Mohd Anuar

STATEMENT 2

This thesis is the result of my own independent work/investigation, except where otherwise stated. Other sources are acknowledged by explicit references.

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December 2014,
Fatahiyah Mohd Anuar

Abstract

Trade marks are valuable intangible intellectual property (IP) assets with potentially high reputational value that can be protected. Similarity between trade marks may potentially lead to infringement. That similarity is normally assessed based on the visual, conceptual and phonetic aspects of the trade marks in question. Hence, this thesis addresses this issue by proposing a trade mark similarity assessment support system that uses the three main aspects of trade mark similarity as a mechanism to avoid future infringement.

A conceptual model of the proposed trade mark similarity assessment support system is first proposed and developed based on the similarity assessment criteria outlined in a trade mark manual. The proposed model is the first contribution of this study, and it consists of visual, conceptual, phonetic and inference engine modules.

The second contribution of this work is an algorithm that compares trade marks based on their visual similarity. The algorithm performs a similarity assessment using content-based image retrieval (CBIR) technology and an integrated visual descriptor derived using the low-level image feature, i.e. the shape feature. The performance of the algorithm is then assessed using information retrieval based measures. The obtained result demonstrates better retrieval performance in comparison to the state of the art algorithm.

The conceptual aspect of trade mark similarity is then examined and analysed using a proposed algorithm that employs semantic technology in the conceptual module. This contribution enables the computation of the conceptual similarity between trade marks, with the utilisation of an external knowledge source in the form of a lexical ontology, together with natural language processing and set similarity theory. The proposed algorithm is evaluated using both information

retrieval and human collective opinion measures. The retrieval result produced by the proposed algorithm outperforms the traditional string similarity comparison algorithm in both measures.

The phonetic module examines the phonetic similarity of trade marks using another proposed algorithm that utilises phoneme analysis. This algorithm employs phonological features, which are extracted based on human speech articulation. In addition, the algorithm also provides a mechanism to compare the phonetic aspect of trade marks with typographic characters. The proposed algorithm is the fourth contribution of this study. It is evaluated using an information retrieval based measure. The result shows better retrieval performance in comparison to the traditional string similarity algorithm.

The final contribution of this study is a methodology to aggregate the overall similarity score between trade marks. It is motivated by the understanding that trade mark similarity should be assessed holistically; that is, the visual, conceptual and phonetic aspects should be considered together. The proposed method is developed in the inference engine module; it utilises fuzzy logic for the inference process. A set of fuzzy rules, which consists of several membership functions, is also derived in this study based on the trade mark manual and a collection of trade mark disputed cases is analysed. The method is then evaluated using both information retrieval and human collective opinion. The proposed method improves the retrieval accuracy and the experiment also proves that the aggregated similarity score correlates well with the score produced from human collective opinion.

The evaluations performed in the course of this study employ the following datasets: the MPEG-7 shape dataset, the MPEG-7 trade marks dataset, a collection of 1400 trade marks from real trade mark dispute cases, and a collection of 378,943 company names.

Table of Contents

Table of Figures

List of Tables

List of Abbreviations

AVR	Average Rank
CBIR	Content-based Image Retrieval
EGCM	Edge Gradient Co-occurrence Matrix
FD	Fourier Descriptor
HIT	Human Intelligence Task
IC	Information Content
IP	Intellectual Property
IPA	International Phonetic Alphabet
IPAS	Industrial Property Automation System
IPO	Intellectual Property Office
IR	Information Retrieval
LCS	Least Common Subsumer
MRR	Modified Retrieval Rank
NLP	Natural Language Processing
NMRR	Normalised Modified Retrieval Rank
OHIM	Office of Harmonization Internal Market
WIPO	World Intellectual Property Organization
ZM	Zernike Moments
ZMEG	Zernike Moments Edge Gradient

List of Publications

Journal Publications

1. Mohd Anuar, F. Setchi, R. and Lai, Y-K. 2013, “Trademark Image Retrieval using an Integrated Shape Descriptor””, Expert Systems with Applications, 40 (1), pp. 105-121.

2. Mohd Anuar, F. Setchi, R. and Lai, Y-K. “Semantic Retrieval of Trademarks based on Conceptual Similarity”, IEEE Transaction SMC Part A: Systems. (accepted)

Conference Publications

1. Mohd Anuar, F. Setchi, R. and Lai, Y-K. 2013. A Conceptual Model of a Trademark Retrieval System based on Conceptual Similarities. 17th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems, Kitakyushu, Japan, pp. 450-459.

2. Mohd Anuar, F. Setchi, R. and Lai, Y-K. 2014. Trademark Retrieval based on Phonetic Similarity. IEEE International Conference on Systems, Man and Cybernetics, San Diego, USA, pp. 1642-1647.

Chapter 1

Introduction

1.1 Motivation

Trade marks are signs that are capable of being represented graphically in the form of logos or brand names, which allow goods or services to be easily recognised and distinguished by consumers. Similar to many other company assets, trade marks can also be subjected to some sort of legal protection. Trade mark registration through an intellectual property office currently provides legal protection for companies and individuals of their registered marks to represent their company, products or services. This legal protection is granted within the jurisdiction(s) covered by the registration office. It therefore provides legal certainty and underpins the rights of the trade mark owner. In principle, the owner of a registered trade mark obtains an exclusive right to the use of the mark, and he or she is provided with more legal protection than is offered by unregistered trade marks.

Trade mark infringement is an intellectual property (IP) crime and an economic problem that requires serious attention. In general, employees in IP-intensive companies provide twice as many sales as their counterparts in non-IP-intensive companies, and in the United States, these types of companies contribute to over a third of the annual Growth Domestic Product (JEC, 2012). The damage caused by this unlawful infringement act includes loss of revenue, reduced profits and additional costs of protection to avoid any future infringement acts on the company. In addition, it can also lead to severe damage to the brand reputation.

In 2012, a total of 3,400 trade mark infringement cases were filed in U.S. District Courts, which excluded the presumably even larger number of cases in which settlements were reached prior to filing the cases (Scott, 2013). In another investigation conducted in 2011 by the U.S. International Trade Commission, it was found that trade mark infringement is the most common IP crime in one of the fastest growing economies in the world, i.e., China (USTC, 2011). Figure 1.1 shows the percentage distribution of the IP-related infringement experienced by U.S. firms worldwide. The same investigation also revealed that U.S.-based company losses were between $1.4 billion and $12.5 billion in 2009; in fact, from 2002–2011, the average annual increase in trade mark litigation cases was 39.8%.

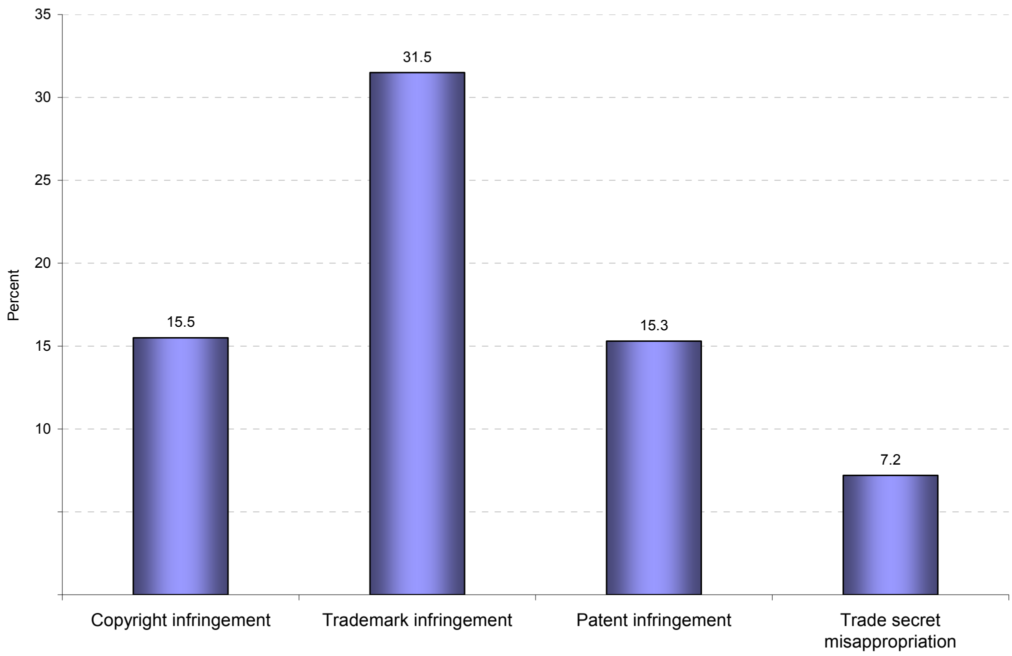


Figure 1.1 Percentage distribution of the IP related infringement experienced by U.S firms worldwide (USTC, 2011)

The number of newly registered and existing trade marks used in the market continues to grow, despite the alarming trade mark infringement statistics. For example, in 2012, the Office for Harmonization in the Internal Market (OHIM) received about 108,000 trade mark applications, an increment of 2% from the previous year (OHIM, 2012b). In the U.S., about 1,867,353 trade marks were registered and maintained during the first quarter of 2013, compared with a total number of 1,752,599 registered and in-use trade marks in the first quarter of 2012 (Dodell, 2013). The newly registered trade mark statistics in the U.S. also climbed by 10% in the fiscal year of 2012 from the fiscal year of 2010 (Dodell, 2013).

Figure 1.2 shows the general trade mark registration process flow by OHIM. It involves three stages, namely the examination stage, the opposition stage and the proof of registration stage (OHIM, 2012a). The examination stage consists of

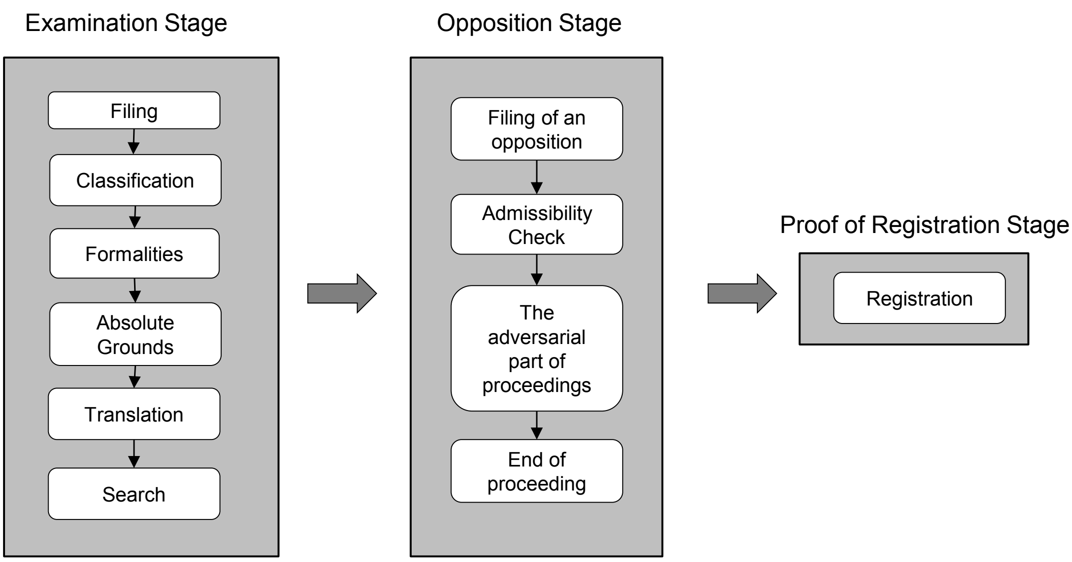


Figure 1.2 Trade mark registration process flow (OHIM, 2012a)

several steps in which one of the steps is the trade mark similarity search. The search process in the trade mark examination stage looks for similar trade mark that has already been registered. In other words, the registration of a trade mark that is found to be identical or similar to any existing trade marks and provides identical or similar goods or services may potentially be opposed, as indicated in section 5 of the Trade Marks Act 1994 (UK, 1994). This is important to avoid infringements, as well as to protect the rights of existing registered trade marks. The opposition stage is the process in which the trade mark is temporarily published online to allow the third party (existing trade mark owners) the right to oppose the new trade marks. In the UK, the examination stage requires approximately six months and the whole application can prolong to additional fifteen more months in the opposition stage (IPO, 2012b). Thus, to avoid future infringement as well as to reduce the possibility of having to deal with opposition cases, which may prolong the registration process, trade mark search requires more advanced mechanism that can detect similar trade marks.

The current practice of examining trade mark similarity search generally involves a very large trade mark database, and the search mechanism to retrieve relevant trade marks does not fully address the similarity examination criteria outlined in the trade mark manual. According to (OHIM, 2012c), trade mark similarity examination should cover three similarity aspects i.e. visual, conceptual and phonetic which are define as the following:

1. Visual: This similarity aspect focuses on the sequence of the letters that constitute trade marks together with the font style variations (for word mark and figurative word mark). For figurative mark, the visual comparison focuses on the silhouette of the marks (OHIM, 2012c).

2. Conceptual: This similarity aspect analyses the semantic content of the trade mark such as the meaning of the trade marks. It focuses on the semantic meaning that the trade marks portrayed towards the public (OHIM, 2012c).

3. Phonetic: This aspect of similarity focuses on the common rhythm and intonation of the trade marks which considers the sound pattern and pitch variations in the syllable that form the trade marks (OHIM, 2012c).

One of the existing trade mark support systems is the Industrial Property Automation System (IPAS), a system developed by the World Industrial Property Organization (WIPO), which provides three trade mark search options: bibliography search, based on the filing date and registration number, phonetic search, based on common prefixes, suffixes and phonetic rules, and logo search, based on the Vienna classification code for figurative trade marks (WIPO, 2014). Although it provides relatively good search support system, the search options i.e. search using bibliography or filing dates are not fully appropriate for trade mark similarity search. A trade mark search system should also allow search based on the three pre-defined similarity aspects i.e. the visual, conceptual and phonetics. In addition to that, the logo search system provided by the current system is mainly based on classification code and not on their visual aspect.

1.2 Trade Marks and Infringement

1.2.1 Categories of Trade Marks

Trade marks exist in various categories. They can be distinctive words and/or images, or even sounds. For example, the OHIM offers trade mark registration for six different forms of trade marks, i.e. word marks, figurative marks, figurative marks with word elements, 3-D marks, colour marks and sound marks (OHIM, 2012a).

Figure 1.3 shows examples of the different forms of trade mark registration offered by the OHIM.

Of these six different forms, the most commonly used trade marks nowadays are word marks, figurative marks and figurative marks with word elements. For example, over the Internet, word marks are also used as domain names and keyword meta-tags to identify products. This, however, has created problems for the established trade mark owners in that their trade marks, e.g. in the form of word marks, can also be used by other companies who wish to benefit from them. Hence, the scope of the study will be within these categories of trade marks, i.e. word marks, figurative marks and figurative marks with word elements.

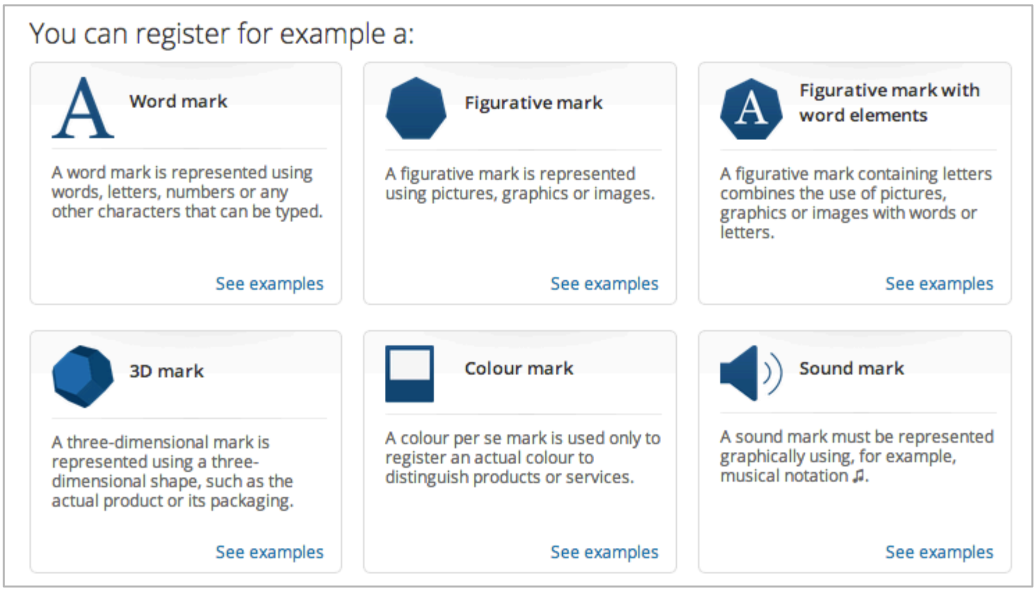


Figure 1.3 A snapshot from the OHIM webpage showing the different types of trade mark registration offered by the office (oami.europa.eu)

1.2.2 Likelihood of Confusion

Both European law and U.S. legal practice (Scott, 2013, OHIM, 2012c) employ the concept of the “likelihood of consumer confusion” to analyse trade mark infringement cases. According to the (OHIM, 2012c), the fundamental concept of the likelihood of confusion refers to the following two possible situations:

1. The public directly confuses the conflicting trade marks;
2. The public makes a connection between the conflicting trade marks and assumes that the products or services are from the same source.

The likelihood of confusion is treated as a legal concept and is assessed globally, i.e. the interdependence between several factors, which includes:

- the similarity of the goods and services;
- the similarity of the marks;
- the strength and reputation of the trade marks;
- the similarity of the marketing channel;
- the evidence of actual confusion.

Thus, this thesis focuses on the second factor, i.e. the similarity of the marks, by developing a trade mark similarity assessment support system that compares trade marks using the three similarity aspects i.e. the visual, conceptual and phonetic aspects.

1.3 Research Objectives

The overall aim of this study is to develop a trade mark similarity analysis support system using the visual, conceptual and phonetic similarities of trade marks. The individual objectives towards achieving this aim are:

i. To develop a conceptual model of a trade mark similarity assessment support system based on visual, conceptual and phonetic similarities;

ii. To develop an algorithm that compares and retrieves trade marks based on their visual similarity;

iii. To develop an algorithm that compares and retrieves trade marks based on their conceptual similarity;

iv. To develop an algorithm that compares and retrieves trade marks based on their phonetic similarity;

v. To develop a methodology to aggregate a trade mark's degree of similarity score from the three aspects of similarity (i.e. visual, conceptual and phonetic).

1.4 Organisation of the Thesis

This thesis is organised as follows:

- Chapter 2 discusses the related work within the scope of this study. It describes existing trade mark search systems together with previous work related to the three aspects of trade mark similarity, i.e. the visual, conceptual and phonetic. This chapter also discusses the evaluation method employed in this study.

- Chapter 3 describes the conceptual model for the trade mark similarity assessment support system, which consists of four main modules.

- Chapter 4 proposes a retrieval algorithm for figurative trade marks and word marks, i.e. trade marks with text, based on their visual similarities. The proposed technique is evaluated using the standard databases previously used in trade mark retrieval research.

- Chapter 5 describes the proposed trade mark retrieval algorithm based on conceptual similarities. The algorithm employs a lexical ontology as the external knowledge source for the comparison process. The proposed algorithm is evaluated using a database comprising 1,400 trade marks from actual infringement cases, as well as a database comprising 380,000 company names. Information retrieval-based evaluations and human collective opinion evaluations are carried out to investigate the performance of the proposed algorithm.

- Chapter 6 describes the proposed trade mark retrieval algorithm based on phonetic similarities. The algorithm employs phonetic features together with a typographic mapping process to compute trade mark similarities. The proposed algorithm is evaluated using a database of 1,400 trade marks from actual infringement cases.

- Chapter 7 describes a methodology that integrates the three trade mark comparison aspects, i.e. the visual, conceptual and phonetic similarities, to aggregate the overall degree of similarity score. The methodology employs the approaches used in a fuzzy logic-based inference system.

- Chapter 8 highlights the contributions and conclusions of this study, as well as outlines future work.

Chapter 2

Literature Review

The work to accomplish the five research objectives defined in the previous chapter requires a diverse range of studies. Thus, this chapter reviews related work that provides key ideas that are applicable to achieving those objectives.

This chapter is organised as follows: Section 2.1 reviews existing trade mark search systems. Section 2.2, 2.3 and 2.4 discuss the related research work in the scope of visual, conceptual and phonetic similarity computation consecutively. Section 2.5 discusses the concept of fuzzy logic inference. Section 2.6 highlights the evaluation methods employed in this thesis and Section 2.7 summarises the chapter.

2.1 Existing Trade Marks Search Systems

According to the trade mark manual (OHIM, 2012c), trade mark similarity examination is performed based on three fundamental aspects, namely the visual, conceptual and phonetic similarities. Although the normal practice covers all three similarity aspects, the research work that has revolved around this area of study in previous years, has mainly focused on an individual aspect of similarity comparison. For example, most of the work that has pioneered research in this area focuses on retrieving trade marks based on only their visual similarity. Such work is mainly dominated by research on vision analysis and content-based image retrieval (CBIR) aiming at developing systems capable of retrieving visually similar trade marks by using low-level features such as shape feature. Some of the work includes the TRADEMARK (Kato et al., 1990), STAR (Wu et al., 1996) and ARTISAN (Eakins et al., 1996), which have been widely referred to by many researchers.

In the TRADEMARK system, the descriptors are derived from graphical descriptor vectors derived from the shape feature. The second system i.e. the STAR, employs the traditional CBIR framework together with a set of shape-based descriptors which includes the Fourier descriptor, gray level projection and moment invariant. In addition to their attempt to solve the problem of retrieving similar trade marks, the system also employs the spatial layout of an image, although this has been found to be extremely challenging. The ARTISAN system also employs a similar approach and uses shape-based feature descriptors and Gestalt-based principles i.e. one of the underlying principles in the study of human perceptual organisation in the school of psychology, to retrieve abstract geometric trade mark design.

The three developed systems previously mentioned i.e. TRADEMARK, STAR and ARTISAN have also inspired other significant research work on trade mark images that focuses on the visual similarity aspects of trade marks. For example, Kim and Kim (Kim and Kim, 1998) employed a moment-based shape descriptor and analysed the distribution model of 90 moments coefficients for all images in their database. Closed contour shape descriptors using angle code strings are employed in (Peng and Chen, 1997) and Jain and Vailaya (1988) who proposed the edge direction histogram and improved the descriptor to be scale and rotation invariant. A comparative study of several commonly used shape-based descriptors for trade mark similarity comparison is carried out in (Eakins et al., 2003). Compositional shape descriptors that combine two or several shape descriptors were also established such as in (Wei et al., 2009, Hong and Jiang, 2008), and also many other related works including (Lei et al., 2008b, Qi et al., 2010, Chen et al., 2007, Goyal and Walia, 2014, Shao and Jin, 2012, Aires et al., 2014).

Despite the amount of work produced so far, this approach is mainly limited to trade marks with figurative marks or logos, although the statistics of registered trade marks in five European countries have shown that only 30% of all trade marks employ logos as their proprietary marks (Schietse et al., 2007). The trade mark similarity issues for the other 70% (trade mark with text element) still remain insufficiently researched.

Available trade mark search systems that focus on trade marks with a text element i.e. a word mark and a figurative word mark, are primarily based on text-based retrieval technology. Such systems return trade marks that match partial or entire words in a query text. To date, the most common retrieval method employed in the existing trade mark search system, which is based on text, as well as in many other multimedia search systems, is known as the keyword-based search. In general, keyword-based search systems look for keywords that have been tagged as pre-defined metadata to items in a database; it then returns words with identical matches. In Europe, OHIM has just recently launched a search system, which provides an option to allow users to search for trade marks in different languages(OHIM, 2012a). The system also provides an advanced search option that offers three search types namely the *word prefix*, the *full phrase* and the *exact match*. The *'word prefix'* mode looks for trade marks with a prefix that matches the query. The *'full phrase'* mode returns trade marks with terms that include the query input whilst the '*exact match'* mode search trade marks that are identical to the query input.

In the United Kingdom, the UK Intellectual Property Office (IPO) also offers relatively similar search options to the OHIM trade mark search service, with an additional option that looks for similar query strings (IPO, 2012a). The IPO search system utilises an approximate string matching technique i.e. a technique that looks for fairly similar pattern in strings, together with several pre-defined criteria, such as the number of similar and dissimilar letters shared by the words and the word lengths, to retrieve similar trade marks.

Although the establishment of the previously discussed systems returns fairly similar or related trade marks, the comparison mechanism employed by such systems still does not cover the holistic aspects of similarity that should be covered during the trade mark examination process i.e. visual, conceptual and phonetic similarities (OHIM, 2012c). The next three sections will thus discuss the related work pertaining to these three aspects, in particular, the approaches and technologies that are closely related to the scope of this study, which have triggered some ideas for the development of work accomplished in this study.

2.2 Visual Similarity Comparison

In the CBIR system, low-level features are utilised for visual similarity and comparison analysis. The low-level features are the primitive visual features that are extracted from the images themselves. The most commonly used features are the shape, colour and texture. Among the three, the shape feature is considered as one of the fundamental and important attributes extracted as a feature descriptor (Hong and Jiang, 2008). Figure 2.1 illustrates the traditional CBIR system for general image retrieval, which consists of two main modules, namely the offline and the online modules. The offline module performs the feature extraction process on a collection of images in the database of a system. One or several features can be

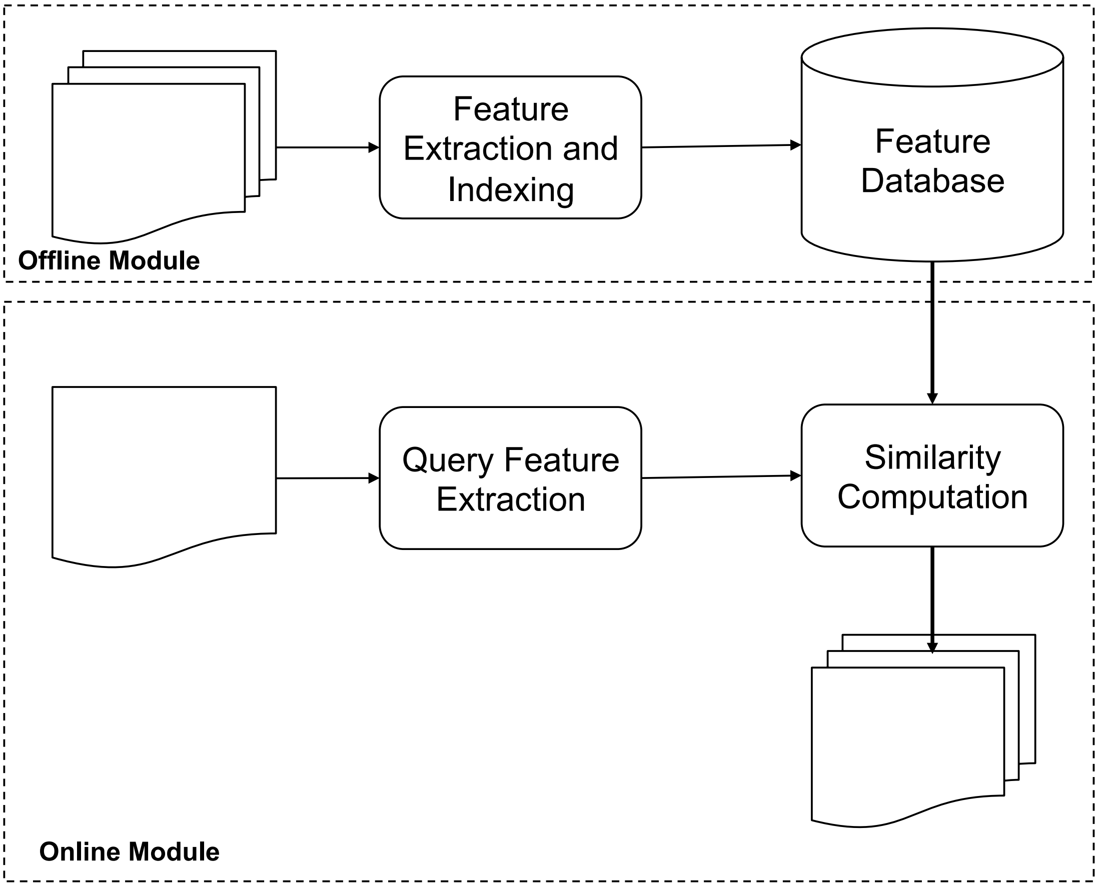


Figure 2.1 Generic CBIR system architecture

used in this process depending on specific applications. For example, in a satellite information system, the texture features are extracted for similarity computation in the system. The online module, which is also commonly referred to as the query module, on the other hand, refers to online feature extraction for query images and the process of computing similarities between the query and database images based on the extracted features.

Previous research findings from psychological studies suggest that shape feature is the single most important feature used by human observers to characterise an image and show that a whole range of familiar objects can be recognised as readily from their silhouette (Schietse et al., 2007). For man-made images such as figurative trade marks or logos, which do not have complicated objects and backgrounds as in natural images, shape feature is considered to be the most prominent visual feature exhibited by such images. Hence, this section will also review shape feature extraction approaches for visual similarity comparison.

In general, shape-based feature extraction approaches can be broadly grouped into two main categories i.e. contour and region-based approaches (Agarwal et al., 2014). The contour-based approach focuses on boundary information, for example, the pixels along the shape's boundary. On the other hand, the region-based approach considers the entire shape region to extract shape features. For instance, all the pixels contained in a shape region are taken into account to obtain the features.

2.2.1 Contour-based Approach

There have been many established descriptors derived using contour-based approaches such as the Fourier descriptor, the wavelet descriptor, and some other simple contour descriptors such as the shape's eccentricity, circularity, and aspect ratio. Among them, the Fourier descriptor (FD) is one of the most commonly used and studied methods (Zhang and Lu, 2004, Folkers and Samet, 2002, Rui et al., 1999, Geevar and Sojan Lal, 2011, Dalitz et al., 2013).

The FD is derived from the spectral transform of shape signatures such as the boundary coordinates or the boundary to centroid distance. The descriptor is then represented using the first few low frequency terms of the transformed signatures. There are various ways to construct the signature signals including x and y boundary coordinates, centroid to boundary distance, and the boundary angle. The performance of the FD is dependent on the shape signature used. For instance, Zhang and Lu (Zhang and Lu, 2002) performed a comparative study of different shape signatures for the computation of the FD and showed that centroid to boundary distance signature gives the best performance compared to other types of signatures. The Fourier descriptor of a signature signal of a function *s(t)* that describes the variation along the boundary of an object, is simply the Fourier transform of the signal and can be calculated as follows:

$$f(n) = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\exp(-j2\pi nt / N), \qquad n = 0,1,\ldots,N-1 \tag{2.1}$$

This results in a series of Fourier coefficients *f(n) i.e.* the Fourier descriptor and *N* which is the number of sampling points of the signature signal.

FD is very practical for data-driven shape retrieval because of its low computational needs (Zhang and Lu, 2004). It also has easier normalisation and information preserving advantages, as well as invariant properties. Nevertheless, FD is highly unlikely to be able to capture local representation of a shape and in addition is sensitive to boundary noise and small variations.

A relatively different way of describing shapes through spectral transformation is the wavelet descriptor (Kunttu et al., 2003, Kith and Zahzah, 2005, Qin and Edwards, 2004). From a psychophysics point of view, the human visual system processes information at different resolutions. Hence, the wavelet transform decomposes signals through a series of dilations and translations of a mother wavelet. The computational method for computing wavelet descriptors is very similar to the method used for the Fourier descriptor computation in which the descriptor consists of the first few transform coefficients of the signature signals. Nevertheless, the wavelet descriptor is sensitive to the starting point of the signature signals. To overcome this problem, for every contour, the point that has the longest centroid to boundary distance will be assigned as the starting point. In addition, the wavelet descriptor also acquires invariant properties.

Several other descriptors which have been regarded as simple contour descriptors and are commonly used in various CBIR applications are the perimeter, the circularity i.e. the ratio of the image area and the square of the image perimeter, the eccentricity, i.e. the ratio of the length of major axis and the length of minor axis and the major axis orientation (Gonzalez, 2010). These simple global descriptors are normally used as filters to eliminate false hits or are combined with other descriptors to discriminate shapes. This is due to their limitation, which can only discriminate shapes with large dissimilarities. Thus, they are unlikely to be used as standalone shape descriptors. For instance, consider the image shown in Figure 2.2, the eccentricity of the shape in Figure 2.2(a) is very close to 1 although it does not correctly describe the shape.

Hence, for this particular example, circularity would be a better descriptor. Nevertheless, the circularity computation on the images shown in Figure 2.2 (b) and (c) produces similar values despite the dissimilar shapes. In this case, eccentricity seems to be a better descriptor. Other simple global contour shape descriptors include convexity, ratio of principle axis, circular variance, and elliptic variance.

C X I

(a) (b) (c)

Figure 2.2 Example of different shape produced by letters for the discussion of simple contour-based descriptors

2.2.2 Region-based Approach

In region-based approach, moments-based shape features have been the most popular method used in many shape-based image retrieval studies (Mehtre et al., 1997, Zhang and Lu, 2004, Wei et al., 2009, Goyal and Walia, 2014, Ma et al., 2011). In general, image moment descriptors are the adaptation of statistical moment analysis, which treats the set of intensity values of the images as its statistical data. There are many different types of image moments such as Hu moments, Legendre moments, Zernike moments (ZM) and Pseudo-Zernike moments. The general form of statistical moment of order (*p,q*) can be expressed in discrete form as follows:

$$m_{pq} = \sum_{x}\sum_{y}\psi_{pq}(x,y)f(x,y)dxdy, \qquad (2.2)$$

where ψ_{pq} is the basis set or moment weighting kernel. The differences between different type image moments lay between the point spread function or the basis function used in the computations. For instance, ZM are theoretically a set of orthogonal moments derived from Zernike polynomials, which are orthogonal over a unit disk.

From a relatively different point of view, moments can also be regarded as the magnitudes of projections of an image onto a set of orthogonal axes given by a set of polynomials functions, and thus contain independent information about the image. In general, moment-based methods have so far yielded superior retrieval performance over other region-based shape descriptors. Among the various types of image moments, ZM has been considered as the best descriptor due to its properties such as lack of noise sensitivity and information redundancy and the most commonly used moment-based descriptors employed in various shape-based applications (Zhang and Lu, 2004, Kim and Kim, 2000, Ma et al., 2011, Goyal and

Walia, 2014). Nevertheless, ZM is highly unlikely to capture the local properties of an image, which might be highly important criteria for certain applications.

Other descriptors, which are commonly regarded as simple region descriptors, are the image area, the compactness and the Euler number (Gonzalez, 2010). Similar to those simple descriptors established using the contour-based approach; these descriptors are normally used for the filtering purpose in the retrieval process.

In conclusion, FD and ZM are the most commonly used descriptors derived from the contour and region-based approaches respectively, in which a lot of established work has been carried out employing these two descriptors. However, ZM has an advantage in terms of its precision performance over FD (Amanatiadis et al., 2011). In addition, ZM is more robust and does not require edge information for computation and hence can be applied to images that do not have clear-cut edges.

2.3 Conceptual Similarity Comparison

This section discusses the related work that has inspired the development of the conceptual similarity algorithm for the trade marks comparison in this study. Such work includes those pertaining to semantic technology, in particular lexical ontology and the word similarity measures that motivate the idea to address the conceptual similarity aspect of comparisons between trade marks.

2.3.1 Ontology

By definition, ontology is a conceptual knowledge representation, which can be described by a set of concepts in a specific domain and the relations between them. From the point of view of knowledge coverage, ontologies are classified as generic or domain specific information. In addition, ontologies have well-defined structures that provide sophisticated knowledge representations. The ontology concepts are not mainly limited to words, but could also be entities, concept attributes, rules, restrictions or other types of high-level information.

Retrieving conceptually similar trade marks requires semantic interpretation, which can be realised using lexical knowledge sources. Lexical knowledge sources include lexicons, thesauri and dictionaries that have been formalised semantically, in accordance with the lexical meaning of the words. In conceptual similarity studies, which are concerned with lexical concepts or meaning, the most commonly used lexical ontology is WordNet.

WordNet is a large electronic lexical database of English language words. This freely available database is one of the most frequently cited lexical resources in NLP literature, with many applications in a wide range of tasks. It was first developed by the Cognitive Science Laboratory at Princeton University, USA. WordNet is constructed based on psycholinguistic theories that model human semantic organisation. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms that act as building blocks known as synsets (Fellbaum et al., 2006). Each synset represents a distinct concept and is linked by lexical relations, such as synonymy, antonymy, hyponymy and meronymy (Miller, 1995). Additionally, each synset also contains a short definition or gloss, which in most cases includes at least one sentence illustrating the usage of the synset members.

To date, the concept of the WordNet lexical ontology has been successfully adapted into over 30 languages (e.g. Dutch, Spanish, German, Basque, Arabic, etc.) (Pociello et al., 2011, Hinrichs et al., 2013, Fernandez-Montraveta et al., 2008, Abouenour et al., 2013, Gonzalo et al., 1999). Additionally, the WordNet ontology has been utilised as an external knowledge source in various domains, such as in medical and inventive design (Fellbaum et al., 2006, Huang et al., 2009, Yan et al., 2011).

The latest version of WordNet, WordNet 3.0, contains 155,287 strings with 117,659 synsets (Wordnet). Table 2.I shows the distribution of words across the parts of speech in WordNet. The lexical semantic representation in WordNet is very useful for natural language processing (NLP) applications, such as semantic similarity measures. Semantic similarity measures are essential to many other NLP applications, particularly word sense disambiguation, text segmentation and information extraction (Sebti and Barfroush, 2008). In a nutshell, the semantic similarity measure represents the degree of taxonomic proximity between the concepts. The score provided by the semantic similarity measure, quantifies this proximity as a function of the semantic relation derived from knowledge sources (i.e. the WordNet ontology).

The following section discusses the most advanced approaches to measuring word similarity.

Table 2.1 Distribution of words across parts of speech in WordNet (Wordnet)

Part of Speech	Unique String	Synsets
Noun	117798	82115
Verb	11529	13767
Adjective	21479	18156
Adverb	4481	3621
Total	155287	117659

2.3.2 Word Similarity Measures

Generally, the computational approach of word similarity measures which are based on ontology fall into three categories, namely the edge counting, the information content and the feature-based approaches (Sánchez et al., 2012). Table 2.2 summarises these approaches and their corresponding measures.

The notion underlying the edge counting approach is that the similarity between two concepts can be computed as a function of the path length that links the two concepts (i.e. the shorter the path, the more semantically similar the concepts are) and the position of the concepts in the taxonomy. This approach views lexical ontologies as a directed graph that links concepts through taxonomic relations, such as the is-a relation. For instance, Wu and Palmer (Wu and Palmer, 1994) consider the position of concepts in the taxonomy relative to the position of the most specific common concept. This approach assumes that the similarity between two concepts is the function of the path length and depth in path-based measures. The taxonomical ancestor between the terms is taken into account i.e. the least common subsumer (LCS), in which the measure counts the number of is-a links from each term to its LCS and also the number of is-a links of the LCS to the root of the ontology.

Similarly, Leacock & Chodorow (Leacock and Chodorow, 1998) also proposed a measure that considers both the number of links that connect the two concepts and the depth D of the taxonomy. The main advantage of the edge counting approach is its simplicity. The computation relies primarily on the directed graph model of a lexical ontology that requires a low computational cost. However, since this approach considers only the shortest path between concept pairs, much of the taxonomical knowledge explicitly modelled in the ontology tends to be omitted

Table 2.2 Summary of word similarity measures based on lexical ontology

Measure	Description	Measures
Edge-based measure	• Semantic similarity depends on the path length and on the position of the concept in the taxonomy. • It employs the concept of common subsumers (i.e. the ancestor concept that subsumes the two concepts). • It is simple to implement. • Two concept pairs with equal length will have the same similarity. • Two concept pairs that share exactly the same least common subsume and equal length will have the same similarity.	• Leacock & Chodrow • $sim(a,b) = -log\,\frac{len(a,b)}{2\times N}$ -len(a,b) is the path length between a and b -N is the maximum depth in the ontology • Wu & Palmer • $\boldsymbol{sim(a,b)} = \frac{\boldsymbol{2\times depth(lcs(a,b))}}{\boldsymbol{len(a)+len(b)+2\times depth(lcs(a,b))}}$ -len(a) and len(b) are the length from each term to their least common subsumer. -lcs(a,b) is the least common subsumer that subsumes a and b -depth(lcs(a,b)) is the length from the root to the least common subsumer that subsumes a and b.
Information Content	• It assumes that the similarity between the two concepts can be derived based on the specificity of the concepts. • The more specific a concept is in the taxonomy, the richer the information content will be. • The information content calculation is derived based on the probability of the occurrence of concepts on the taxonomy. • Two pairs with similar lcs and a cumulative IC between two concepts may have the same similarity.	• Resnik • $\boldsymbol{sim(a,b) = IC(lcs(a,b))}$ -IC(lcs(a,b)) is the negative log of its probability occurrence. • Lin • $\boldsymbol{sim(a,b)} = \frac{\boldsymbol{2\times IC(lcs(a,b))}}{\boldsymbol{IC(a)+IC(b)}}$ • Jiang & Conrath • $\boldsymbol{sim(a,b) = IC(a) + IC(b) - 2(IC(lcs(a,b)))}$
Feature-based Measure	• It is independent of taxonomy and the subsumers of the concepts. • It assumes that each concept comes with specific features that can be employed to measure similarity. • It is defined as the 'glosses' (i.e. the definitions of concepts as the features that represent the concepts). • The computational complexity is very high.	Lesk -the similarity between 2 concepts is computed from the overlapping words existing in the corresponding glosses in WordNet

during computation. Another known problem of this approach is the assumption that all links in the taxonomy represent a uniform distance.

The information content-based measure approach, on the other hand, makes use of the notion posited by information content (IC) theory, that is, by utilising the appearance probabilities of each term in the taxonomy, which is computed from their occurrences in a given corpus. For instance, the IC of a term ‘x’ is computed according to the negative log of its probability of occurrence, as shown in equation 2.3, in which the probability value is estimated as in equation 2.4:

$$IC(x) = -\log p(x) \tag{2.3}$$

$$p(x) = \frac{frequency(x)}{M} \tag{2.4}$$

where M is the total number of terms that exist in the taxonomy. This measure indirectly reflects the specificity that the higher the IC value is, the more specific the concept in the taxonomy is. In this manner, infrequent words are considered more informative than common ones.

Several measures have been established using this notion, such as Resnik (Resnik, 1995), Lin (Lin, 1998) and Jiang and Conrath (Jiang and Conrath, 1997). Resnik proposed that semantic similarity depends on the amount of shared information between two terms, which is represented by their LCS in an ontology. This measure further assumes that two terms are semantically similar in proportion to the amount of information they share (i.e. the more common information the two concepts share, the more similar the terms are). Similarity measures are then based on the information content of each concept. For two given terms, the similarity depends on the information content that subsumes them in the taxonomy.

Lin, Jiang and Conrath extend Resnik's work by including the IC of both terms in the similarity computation. Lin proposed that the similarity between the two terms should be measured as the ratio between the amount of information they share and the independent information that describes the terms. The measure proposed by Jiang and Conrath is based on the length of the taxonomical links as the difference between the IC of a concept and its LCS. This measure computes the similarity distance between two pairs by subtracting the sum of the IC of each term alone from the IC of its LCS. Both Lin and Jiang and Conrath measures, scale the information of subsuming concept by using the IC of the individual concepts to provide fined distinction for those concepts that share the same least common subsumer. Lin performs such distinction via ratio and Jiang and Conrath with difference operation.

Unlike the previously discussed measures, the feature-based measure is independent of the taxonomy and the subsumers of the concepts. Instead, it attempts to exploit the properties of the ontology to obtain the similarity values. It is based on the assumption that each term is described by a set of words indicating its properties or features, such as its definitions or 'glosses' in WordNet. The more shared features or characteristics and the fewer non-shared features two terms have, the more similar they are. A commonly used measure utilising this approach is the Lesk measure (Banerjee and Pedersen, 2002) which uses the glosses in WordNet as a unique representation of the underlying terms. It computes semantic relatedness by finding and scoring overlapping features between the glosses of the two terms, as well as terms that are directly linked to them according to the lexical ontology.

In conclusion, the presented word similarity measures, i.e. the ones based on edge counting, information content and feature-based approaches are generally recognised by their simplicity and computational efficiency as they only exploit the semantic network provided by the ontology. However, in terms of computational complexity, the edge counting measures are the simplest ones. The feature-based approaches tend to rely on features, i.e. the synonym sets or the glosses. As a consequence, their applicability and accuracy depend on the availability of this information. The information content approaches on the other hand, rely on semantically annotated textual data, which aim to capture implicit semantics as a function of the concept distribution in lexicons. Hence, in general, there are no absolute best performance measures. Instead, different word similarity measures provide different performances in different applications. Hence, a comparative performance study of these measures will be also investigated on the database employed in this study.

2.4 Phonetic Similarity Comparison

This section discusses the related work concerning the phonetic similarity aspects of trade marks. Similar to the conceptual similarity aspect, the phonetic similarity is also relatively new in the field of trade mark study, which is still under researched, hence the scope of the discussion will be based on a relatively different area of study but which still shares similar concepts and objectives. Thus, the established work on phonetic similarity algorithm measures in the areas of genealogy and historical linguistics are reviewed in this section.

2.4.1 Phonetic Algorithm in Genealogy Study

A phonetic algorithm computes the similarities between strings based on their articulatory, acoustic and perceptual similarities between vowels and consonants. In genealogy, phonetic algorithms are applied to name-matching applications, which attempt to retrieve closely similar names despite spelling variations (Draganov et al., 2008). One of the earliest algorithms for phonetic matching is Soundex, which was originally used in such applications. Soundex was developed by Odell and Russell, and was patented in 1918 (Hall and Dowling, 1980). The algorithm employs a code-based transformation on the sound of each letter to translate a string into a canonical form of, at most, four characters, while maintaining the first letter. This approach is a somewhat primitive way to preserve the salient features of the phonetic pronunciation of the word. For example, the Soundex codes for the trade marks *SWISS TALER* and *Svizze-rotaler* are S-234 and S-126, respectively. However, the algorithm cannot provide the rankings of matches but can only conclude whether they are similar or dissimilar. This limits its capability for retrieval applications that require ranking ability. Another major problem with Soundex is that it keeps the first letter; hence, any error at the beginning of a name will result in a different Soundex code. Nevertheless, the Soundex application still continues even in other languages such as the ones in (Ousidhoum and Bensaou, 2013, Bhatti et al., 2014). Table 2.3 shows the transformation codes used in the Soundex algorithm.

Relatively similar to the approach used in Soundex, the Phonix algorithm also employs a string transformation that maps letters into specific codes. However, it is far more complex than Soundex (Pfeifer et al., 1996) and consists of more than a hundred transformation rules. In addition, the algorithm tends to also include a pre-processing that aims to improvise the encoding quality. The main difference between the two algorithms is that Phonix pays more attention to the ending sound of the word. Besides, this algorithm performs well only with English words.

Table 2.3 Transformation code used in Soundex algorithm

Numeric Code	Letter
0	a,e,I,o,u,y,h,w
1	b,p,f,v
2	c,g,j,k,q,s,x,z
3	d,t
4	L
5	m,n
6	R

Another commonly used phonetic algorithm that employs a similar approach is the Metaphone algorithm (Philips, 1990). The Metaphone algorithm transforms the original word using English pronunciation rules, which makes conversion rules much more complicated. However, this algorithm loses relatively less information than the approaches discussed before, as the letters are not divided into groups. Unlike Soundex, which operates on a letter-by-letter scheme, the Metaphone analyses both single consonants and groups of letters called diphthongs according to a set of rules for grouping consonants, prior to mapping the groups to the Metaphone codes. The final outcome, however, is not truncated into a specific number of codes, as with Soundex or Phonix. An improved version of Metaphone is called Double Metaphone. Unlike the original, the Double Metaphone algorithm generates two sets of codes from each word (Philips, 2000). The pair of codes corresponds to the basic version of the word's pronunciation along with an alternative version. The algorithm also has a large number of different rules that take into account the origin of words, focusing on those from Eastern Europe, Italy, and China.

2.4.2 Phonetic Algorithms in Computational Linguistics

In a relatively different area of study, i.e. computational linguistics, the phonetic algorithms are commonly utilised to find similarities between languages. An example of such work includes the study of similarities between cognates (i.e. words from different languages which share the same linguistic origin and etymology) (Kondrak, 2004, Schepens et al., 2013).

One of the earliest phonetic algorithms, developed in this field is the Covington algorithm (Covington, 1998). This algorithm creates an alignment of words by matching or skipping word segments and assigning a cost or penalty to each match or skip. The penalties assigned in the algorithm are based on similarities between vowels, consonants, and glides (e.g. the letter *w* and *y*). The algorithm, however, does not rank the relative importance of phonological features nor does it weigh vowel and consonant mismatches based on their features, i.e., the specific location at which the sound is formed in the mouth. Thus, a mismatch between *p* and *b* has the same penalty as a mismatch between *p* and *r*. Table 2.4 shows the penalty metrics used by Covington.

Somers introduced an algorithm that focuses on the problem of comparing the speech of a child to mature adult speech (Somers, 1999). The algorithm helps to automate the process of matching childhood pronunciations to the correct adult word. It employs the similarities between vowels, consonants and glides, together with information on stress, and some fundamental binary features between phonemes (the smallest phonetic units in the language). In addition, Somers also performs an exhaustive search strategy to find the best string alignment based on a binary search tree as part of his phonetic algorithm. The algorithm is also tested on

Table 2.4 Penalty metrics used by Covington (Covington, 1998)

Penalty	Conditions
0	Exact match of consonants or glides (w,y)
5	Exact match of vowels (reflecting the fact that the aligner should prefer to match consonants rather than vowels if it must choose between two)
10	Match of two vowels that differ only in length, or I and y, or u and w
30	Match of two dissimilar vowels
60	Match of two dissimilar consonants
100	Match of two segments with no discernible similarity
40	Skip preceded by another skip in the same word
50	Skip not preceded by another skip in the same word

the Covington's test dataset. The accuracy result obtained by Somers is comparable to those achieved by the Covington's algorithm.

One successful phonetic algorithm that used a fairly similar approach is the ALINE algorithm which was developed by Kondrak (Kondrak, 2003) and has been used in various studies (Savva et al., 2014, Wang et al., 2013, Kondrak and Dorr, 2006). ALINE consists of two fundamental components: a method for choosing an optimal alignment and a similarity function that uses linguistic feature analysis measurements based on phonological features. The approach is designed to align phonetic sequences for many different computational-linguistics applications and, in fact, was initially designed to identify cognates in vocabularies of related languages, such as the word color in English and couleur in French. A dynamic programming algorithm is employed to perform the alignment and similarity computation task efficiently. The algorithm represents phonemes from a word string as vectors with phonetic features. The word string is transcribed using the International Phonetic Alphabet (IPA) transcription standard. Each phoneme segment is then encoded using a designed scheme that consists of a combination of upper, lower case letters and binary numbers. The segment consists of 12 phonological saliences, some of which consist of multi-valued features. Table 2.5 list the phonological saliences used in the algorithm and Table 2.6 lists the multi-valued features that belong to their respective saliences. The graphical representations of the "place" saliences, which concern sound articulation features, are shown in Figure 2.3.

Table 2.5 Salience features used in the ALINE algorithm (Kondrak, 2003)

Syllabic	Place
Voice	Nasal
Lateral	Aspirated
High	Back
Manner	Retroflex
Long	Round

Table 2.6 Multi-valued saliences and their corresponding features (Kondrak, 2003)

Salience Features	Features
Place	Bilabial, labiodental, dental, alveolar, retroflex, palato-alveolar, palatal, velar, uvular, pharyngeal, glottal
Manner	Stop, affricate, fricative, approximant, high vowel, mid vowel, low vowel
High	High, mid, low
Back	Front, central, back

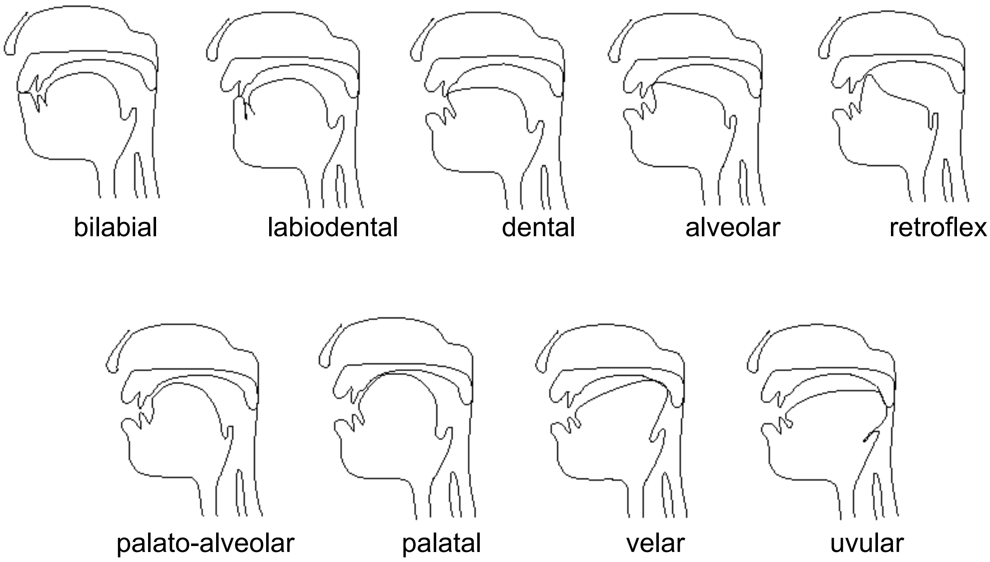


Figure 2.3 Graphical representation of some of the features employed in ALINE (Kondrak, 2003)

ALINE then assigns a similarity score to each pair of phoneme segments based on a weighted multi-feature analysis of both consonants and vowels. Thus, ALINE provides a stronger scientific basis for the metrics used in the algorithm and eliminates some of the innate weaknesses of the Covington algorithm. In addition, a comparative study performed on this algorithm against the Somer and Convington algorithms shows that ALINE produces the best performance (Kondrak and Dorr, 2006) .

Although ALINE is first developed for linguistic applications, in which the words involved are real words i.e. known words, ALINE can also be used for out of vocabulary words and still produces usable results. For example, it has been employed in the study of similarity comparisons in drug names (Kondrak and Dorr, 2006) and has been incorporated as the basis of a system developed for the U.S. Food and Drug Administration for the detection of confusing drug names.

The development of ALINE has also addressed some of the issues with other algorithms, such as Soundex. First, it uses the entire string instead of truncating a word to a limited number of characters; second, it involves vowels in the matching process instead of dropping them out; and third, it uses decomposable speech production features instead of numbers. In this approach, phonetic similarities are established between two words as a by-product of finding an optimal match between their corresponding phonetic features.

Regardless of the similar objectives of the work established in linguistics and genealogy, trade mark phonetic similarities remain a unique problem. The similarities in trade marks are assessed as a whole and trade marks are not limited to only one word. Thus, a specific algorithm that phonetically compares a collection of words is needed. Moreover, trade marks may also contain symbols or special characters, which, according to the trade mark manual, have phonological properties.

2.5 Fuzzy Logic

The work discussed in the previous three sub-sections, i.e. Sections 2.2, 2.3 and 2.4, provides some established yet related work that lays some background foundation and generates some ideas for finding solutions to the issues of individual aspects of trade mark comparisons namely visual, conceptual and phonetic similarities. This section thus describes the concept of fuzzy logic that provides a mechanism to further integrate the three aspects of trade mark similarities in a systematic way, that is by using a fuzzy inference model, to aggregate the overall trade mark degree of similarity. Several alternative approaches are also discussed at the end of the section.

2.5.1 Fuzzy Logic

The concept of fuzzy logic was first introduced by L. A. Zadeh in 1965, (Zadeh, 1965) as a mathematical tool for dealing with uncertainties. From the point of view of set theory, the concept of fuzzy logic is merely an extension of the classical or crisp set concept in which every preposition must be either *'true'* or *'false'*, or in a range of values. Instead, the concept of fuzzy logic as fuzzy set is a fundamentally broader set compared with the classical or crisp set. It asserts that every preposition can simultaneously have a certain degree of a membership function of the *'true'* or *'false'* class. The membership function is a generalisation of the indicator function that maps items in classical/crisp set to the fuzzy set and vice versa. For instance, in the classical set concept involving two possible preposition values, the membership function can either have a non-membership value i.e. 0, or a membership value i.e. 1. On the other hand, fuzzy logic allows the membership functions to have any value in between [0,1]. The value 0 represents a complete non-membership, and 1 being a complete membership and the values in between are partial representations of the membership functions.

The inference system or rule-based system developed based on fuzzy logic uses fuzzy set operations and properties for reasoning tasks. The system also consists of a fuzzy knowledge base or a commonly known fuzzy rule base. The fuzzy rule concept generally has two components, namely the *IF* component i.e. the antecedent, which describes a condition and the *THEN* component i.e. the consequent, which describes a conclusion (Jang et al., 1997). The generic rule statement is shown as the following equation:

IF <antecedent>, THEN <consequent> (2.5)

In the context of human oriented tasks/processes that require approximate human reasoning/decision making based on experiences and insights, the human inference system tends to use verbal variables to create verbal rules, which have similar forms as in Equation (2.5). Fuzzy logic then adapts these verbal rules together with the verbal terms and variables to model the human inference system to a computer-based system. Since the terms and variables used in the human inference system are normally *'fuzzy'* rather than precise, the fuzzy inference system is highly applicable in the course of this application. The verbal terms and variables can therefore be expressed mathematically as membership degrees and membership functions together with symbolic verbal phrases rather than numeric values. Indirectly, it provides a systematic mechanism to utilise uncertain and imprecise information generated by human judgments.

The implementation of the fuzzy inference approach in various applications commonly involves two inference models i.e. the Mamdani, which is based on the fuzzy relational model and the Takagi-Sugeno inference model (Akgun et al., 2012). The most obvious difference between Mamdani and Takagi-Sugeno models is the way the crisp output is generated from the fuzzy inputs. The Mamdani model uses the technique of defuzzification for output aggregation. On the other hand, Takagi-Sugeno model employs weighted average for output aggregation. Although, Takagi-Sugeno model has better processing time since the weighted average replace the time consuming defuzzification process, the expressive power and interpretability of Mamdani model output is lost in the Takagi-Sugeno model since the consequents of the rules are not fuzzy. Due to the interpretable and intuitive nature of the rule base, Mamdani model is widely used in various applications particular for decision support application. Therefore, the Mamdani inference model fits the objective and aims of this study due to its intuitive and linguistic model applicability, which makes it very well suited for human oriented based application.

Other alternative approaches, which consider multiple criteria in the computation of final output, include the work in multi-criteria decision making (MCDM) analysis and predictive data mining i.e. data classification. The aim in MCDM analysis is to provide decision makers the most appropriate recommendation based on several criteria such as attributes, features and etc. Among various techniques used in MCDM, the technique for ordered performance by similarity to ideal solution (TOPSIS) is an algorithm that fit the context of this thesis study (Wang and Wang, 2014). TOPSIS rates every alternative using a set of pre-defined criteria by maximizing the distance to the worst solution and minimizing the distance to the ideal solution. Both ideal and worst solutions are first identified in which the ideal solution is the ones, which possess the highest value in each criteria and the worst solution is vice versa. In data mining, classification algorithms used for automatically assigned an object to its class based on their multi-features include k-Nearest Neighbours (k-NN), C4.5 and Support Vector Machine (SVM). The k-NN is a simple and intuitive algorithm which finds the closest objects in the training set (in comparison to the query object) and classifies the query object to the most common class among the closest objects (Piro et al., 2012). The similarity between objects is computed using a distance metric such as the Euclidean or Manhattan metrics. The C4.5 algorithm is based on a classification model in the form of a decision tree. It adopts a greedy strategy that employs entropy measure for the construction of the tree in a top-down fashion. (Kumar and Verma, 2012). The SVM performs classification by separating the training data based on the decision boundary that maximises distances between data points. It first transforms the data into higher dimensional space, which can be linearly separated (Kumar and Verma, 2012).

2.6 Evaluation Method

This sections reviews standard evaluation measures employed in information retrieval community and a new evaluation method that uses human collective survey/opinions.

2.6.1 Information Retrieval Evaluation

In information retrieval (IR), the common practice of evaluating the performance of a retrieval system is to conduct experiments on test collections to compare the relative effectiveness of different retrieval approaches using a number of evaluation measures. In general, a test collection consists of a collection of documents, a set of sample queries, and a set of relevant documents (the ground truth set), which have been manually identified for each query. Thus, for each query, the system evaluation measure quantifies the similarity between the set of documents retrieved and the set of known relevant documents. This provides an estimation of the goodness of the retrieval strategy. Hence, this section describes the most commonly used evaluation metrics in system-based retrieval performance evaluation.

Recall and precision are the most common retrieval performance evaluations used by the IR community (Manning et al., 2008). Precision is the ratio of the number of relevant retrieved items and the total number of retrieved items and recall is the proportion of the relevant documents out of all documents retrieved from the collection. The measures are defined by the following equation:

$$\text{Precision}=\frac{\text{No of relevant retrieved items}}{\text{No of retrieved items}} \tag{2.6}$$

$$\text{Recall}=\frac{\text{No of relevant retrieved items}}{\text{No of relevant items in the database}} \tag{2.7}$$

Alternately, the precision and recall score can also be calculated from the classification confusion matrix. The confusion matrix is shown in Figure 2.4 where TP, TN, FP and FN are the true positive, true negative, false positive and false negative respectively. The derivation of the precision and recall from this matrix is given by the following equation:

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \tag{2.8}$$

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{2.9}$$

		Predicted Class	
		Positive	Negative
Actual Class	Positive	**TP**	**FN**
	Negative	**FP**	**TN**

Figure 2.4 The confusion matrix for binary classification

Other commonly used measures are the R-precision score and the accuracy score. The R-precision score is the precision score at the R_{th} retrieval position and the accuracy score is defined as follows:

$$\text{Accuracy}=\frac{\text{TP+TN}}{\text{Total Data}} \tag{2.10}$$

The performance of a retrieval system with predefined classes is also commonly measured using the bull's eye score (Bhuptani and Talati, 2014). The measure is defined as follows:

$$\text{Bull's eye score} = \frac{R}{2 \times \text{relevance items in the database}} \tag{2.11}$$

where R is the number of relevance retrieved items in the first 2 x relevance items in the ranked results.

Another performance measure that pays more attention to the ranking capability of a retrieval system and is also considered as a measure of retrieval effectiveness is called the normalised modified retrieval rank (NMRR) (Candan and Sapino, 2010). The NMMR score signifies the performance of a retrieval system for a specific query. It indirectly combines the precision and recall to obtain a single objective score for a specific query. For each relevant item to the query in the retrieval list, it requires a rank value assignment, *rank(k)* which is equivalent to their retrieval rank result, provided that they are in the top *K* rank in which *K=min[2N(q),2M),* where *N(q)* is the number of relevant images to the q in the database and M is the maximum number of relevant images exist in the database across all queries. The average rank of query *q* is then defined as:

$$AVR(q) = \sum_{k=1}^{N(q)} \frac{rank(k)}{N(q)} \tag{2.13}$$

The modified retrieval rank MRR(q) is then computed as:

$$MRR(q) = AVR(q) - 0.5 - 0.5 * N(q)\ , \tag{2.14}$$

and finally the normalised modified retrieval rank, which is used in this study, is as follows:

$$\mathrm{NMRR}(q) = \frac{\mathrm{MRR}(q)}{K + 0.5 - 0.5 * N(q)} \quad (2.15)$$

This study also employs an F-score measure, which is computed based on the weighted harmonic mean of the precision and recall score, and defined as follows:

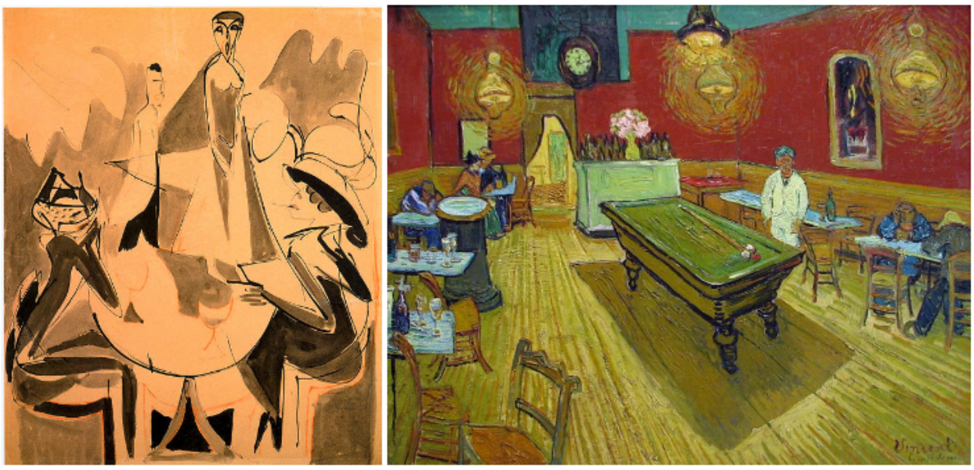
$$\text{F-score} = \frac{2TP}{TP+FP+TP+FN} \quad (2.16)$$

2.6.2 Human Collective Opinion Evaluation

Crowdsourcing is an open call task recently used in information retrieval study; and has been proven to produce fast and reliable results in a cost-effective way (Fadzli and Setchi, 2012, Snow et al., 2008, Corney et al., 2010). In Crowdsourcing, the task is sent to a large group of people known as workers to solve a problem or complete a task. This task, commonly known as a human intelligence task (HIT), is a small portion of an even larger task, distributed among a larger group of workers, who apparently have no contact among them. Payment is made to the worker in exchange for completion of the task upon the HIT completion. Figure 2.5 shows an example of HIT used in an IR study which concerns human similarity perception (Kovashka and Lease, 2010). This study employs the Amazon Mechanical Turk Crowdsourcing service to conduct the evaluation using this approach.

2.7 Summary

In order to examine the similarities between trade marks, their visual, conceptual and phonetic aspects must be investigated. Although these aspects are clearly defined in the trade mark manual, research that has involved all three aspects is still limited. The comparison mechanism employed by existing systems has yet to cover



How similar is the artistic style in the paintings above?

☐ Very similar
☐ Somewhat similar
☐ Neither similar nor dissimilar
☐ Somewhat dissimilar
☐ Very dissimilar

Figure 2.5 HIT example used in an IR related study (Kovashka and Lease, 2010)

the holistic aspects of similarity that is normally assessed during the examination of trade mark similarity.

Shape feature is the most important low-level feature used for the visual comparison of figurative trade marks. It is represented in the form of a descriptor that can be derived using region or contour-based approaches. Moment-based descriptors have a lot of advantages, especially in terms of their precision performance. Nevertheless, they have not yet captured the local property of a shape, which is very important for the trade mark visual similarity comparison.

Advances in semantic retrieval technology provide an opportunity to overcome the limitations of a traditional keyword-based search system. Semantic retrieval, which employs external knowledge sources such as ontologies, provides a mechanism for comparing trade marks based on their conceptual aspect. A lexical ontology that contains lexical knowledge source relationships between its entries forms the structural framework for organising lexical information, which is useful for trade mark conceptual similarity computation.

Phonetic algorithms have been widely employed in the areas of genealogy and computational linguistics for name-matching applications and language similarity studies, respectively. Algorithms established from genealogy studies are designed using the rule-based approach. In computational linguistics, such algorithms are based on human speech production and employ phonological features. Therefore, this approach provides a stronger scientific basis for the phonetic similarity computation between trade marks.

In the context of a human-oriented task/process that requires approximate human reasoning/decision making based on experiences and insights, fuzzy inference has shown remarkable performance. Its natural modelling capability, which can mimic the very complex system underlying the human mind, may provide a mechanism to aggregate the overall similarity between trade marks. Furthermore, the concept of fuzzy logic has long been recognised in many engineering and non-engineering applications.

Standard information retrieval measures, such as precision, recall and F-scores, have long been utilised to evaluate the performance of retrieval systems. A relatively new evaluation approach based on human collective opinions using Crowdsourcing has been proven to produce fast and reliable results, which would also be beneficial for the evaluation of trade mark similarity-based applications.

Chapter 3

Conceptual Model of a Trade Mark Similarity Assessment System

This chapter addresses the first research objective, as outlined in the first chapter in this thesis. It proposes a conceptual model of a trade mark similarity assessment support system. The chapter is organised as follows. Section 3.1 discusses the trade mark similarity aspects performed during trade mark examination process, as explained in the trade mark comparison manual from the Office of Harmonization for Internal Market (OHIM), a European Union agency responsible for registering trade marks and designs that are valid for 27 European countries (OHIM, 2012c). It also describes the comparison requirement needed during the examination process. Section 3.2 introduces the proposed conceptual model together with the main modules and a framework of the proposed support system. Section 3.3 summarises this chapter.

3.1 Trade Mark Similarity Assessment

The trade marks (in the scope of this study) are categorised by OHIM (OHIM, 2012c) in four categories, namely the word mark, figurative word mark, purely figurative mark and pure figurative mark with figurative word mark (see Figure 3.1). The manual outlines the examination criteria performed during trade mark examination based on the visual, phonetic and conceptual similarities, assessed during trade mark examination.

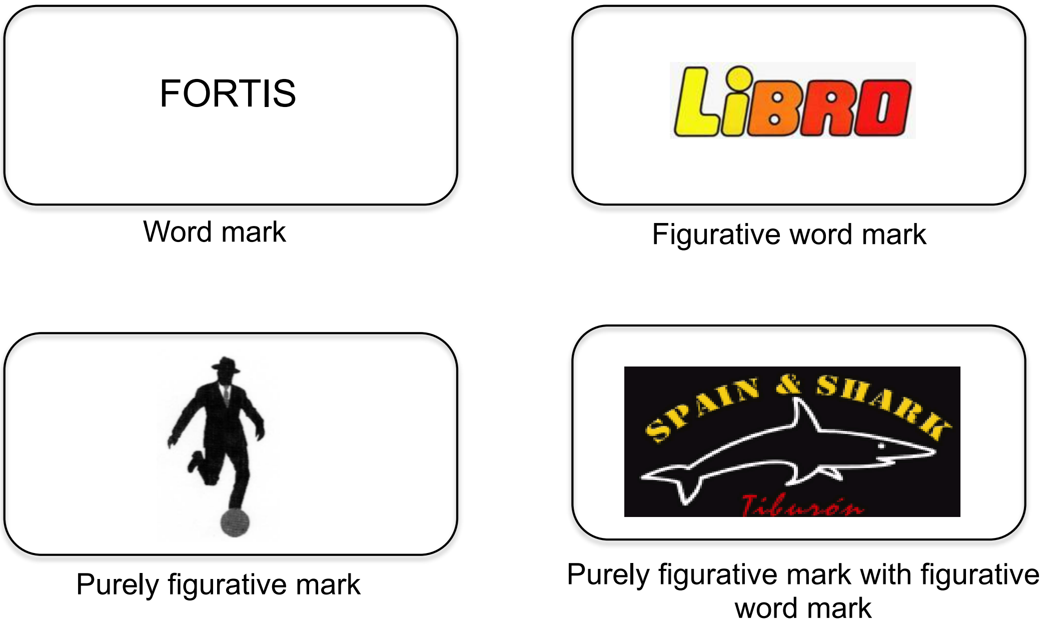


Figure 3.1 Different types of trade mark categories (OHIM, 2012c)

Visual comparison focuses on the appearance of the marks and how they are perceived to be visually similar. For the phonetic comparison aspect, the examination examines the auditory perception from the sound produced when human utters the trade marks in comparison. In this aspect, the trade marks may look visually dissimilar i.e. different spelling but they can produce similar sound e.g. *"poll"* and *"pole"*. The conceptual similarity comparison deals with the semantic content portrayed by the trade marks. For example, trade mark that contains the word *"baggage"* shares similar concept with the word *"luggage"* because they evoke the same meaning.

The similarity comparison process is made more complicated with the fact that trade marks exist in many types i.e. word mark, figurative word mark, pure figurative mark. This is because different types of trade mark require different pre-processing steps, different features to represent them and also different comparison processes.

The following sub sections discuss the examination guidelines for each aspects of similarity comparison.

3.1.1 Visual Comparison

Since trade marks consist of several types, the visual comparison between those trade marks requires different comparison requirement and analysis. The following section discusses the comparisons for each trade mark type.

Comparison of a word mark with a word mark

In general, for trade mark of word mark type, one of the most important criteria is the sequence of the letters and the structure of the words in comparison. However, this criterion is analysed with the end in minds that human being or the average customer often perceives mark as a whole. This assumption agrees with one of the most famous theory on how human perceives and groups things visually, the Gestalt theory. Thus, small differences i.e. missing one or two letters when the signs in comparison have a common structure will not be sufficient to rule dissimilarity. Table 3.1 shows some of the cases where the marks in comparison are found to be visually similar.

Table 3.1 Examples of visual similarities for word mark cases (OHIM, 2012c)

Earlier sign	Contested sign	Case No
CIRCULON	CIRCON	T-542/10
MEDINETTE	MESILETTE	T-342/10
FORTIS	FORIS	R 0049/2002-4
ARTEX	ALREX	T-154/03
BALLYMANOR	BallyM	R 0391/2010-1
MARILA	MARILAN	R 0799/2010-1
EPILEX	E-PLEX	T-161/10
CHALOU	CHABOU	T-323/10

Comparison of a word mark with a figurative word mark

The first comparison criteria between word mark and figurative word mark focuses on the criterion discussed in the previous paragraph that is to check on the sequence of letters and the structure of the words. The next criterion is to examine whether the figurative word mark is depicted in a highly stylised font. The word mark font is normally the standard word font found in word processing tool. Thus, if the figurative word mark resembles similar font i.e. low variation of font style, the marks may found to be similar. Examples of the cases where the marks in comparison are found to be visually similar are shown in Table 3.2.

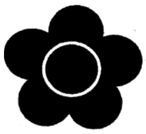
Comparison of a purely figurative-mark with a purely figurative-mark

The major criterion when comparing two purely figurative trade marks is whether they have similar contour. For purely figurative trade marks that have more than one component, the marks will be considered as visually similar if any of the

Table 3.2 Examples of visual similarities involving word marks and figurative word marks (OHIM, 2012c)

Earlier sign	Contested sign	Case No
VITAFIT	VITAL& FIT	T-552/10
Hella	HELL	T-522/10
vitafresh	vitasteam	R 0399/2009-1

Table 3.3 Examples visual similarities involving purely figurative mark (OHIM, 2012c)

Earlier sign	Contested sign	Case No
		T-379/08
		B 1 157 769
		T-523/08

components match or have similar contour. Table 3.3 shows three examples where the trade mark pairs are found be visually similar.

Comparison of a figurative word mark with a figurative word mark

The figurative word marks comparison process shares similar criterion with the word mark and figurative word mark comparison. There are two major criterions, first the comparison on the sequence of letters and the structure of the words, and follows with analysis of the font style used. The marks will be considered similar only when the first criterion is fulfiled and there are no variations in the font style of the marks (the letters are represented in highly stylised fonts). Table 3.4 shows such cases.

Comparison of a purely figurative-mark and word element with a purely figurative mark

This visual comparison adapts the same criterions hold for the 3rd and 4th cases presented above.

Table 3.4 Examples of visual similarities concerning figurative word marks (OHIM, 2012c)

Earlier sign	Contested sign	Case No
LIBERO	LiBRO	T-418/07
alpine	ALPINE PRO SPORTSWEAR & EQUIPMENT	T-434/10 (appeal dismissed)

3.1.2 Conceptual (Semantic) Comparison

According to the manual, two trade marks will share similar concept when they are perceived to have the same semantic content. The semantic content defined here is the meaning, evocation and representation of the marks conceptually. It revolves around the questions of what it means or what it evokes. Thus, in the event involving trade marks that contains words, the very first step that an examiner should do is to look up the explanation of that word in dictionaries and/or encyclopaedias. If the word is in the dictionary/encyclopaedias, then the described meaning in those lexicons will be its semantic content. The conceptual comparison in the scope of this study offers a new research direction, as it has never been investigated in the past. Examples of trade mark cases with conceptual similarity are shown in Table 3.5. The conceptual comparison addresses in the scope of this study involves the following trade mark types:

1. Word mark with word mark
2. Word mark with figurative word mark
3. Figurative word mark with figurative word mark

Table 3.5 Examples of conceptual similarity (OHIM, 2012c)

Earlier mark	Contested mark	Case No
SECRET PLEASURES	PRIVATE PLEASURES	R 0616/1999-1
ORPHAN EUROPE	ORPHAN INTERNATIONAL	R 1142/2009-2

3.1.3 Phonetic Comparison

The phonetic comparison examines the phonological properties of the text represented by the trade marks. Phonetic comparison also offers a relatively new research direction for work that deals with trade marks i.e. trade mark retrieval, as it involves a different similarity concept from the most commonly investigated that is the visual similarity. Phonetic comparison looks for the similarity in the pronunciation of the words particularly the common ‘rhythm’ and ‘intonation’. The ‘rhythm’ is defined as the arrangement of words into a regular sequence of stressed and unstressed syllables. The ‘intonation’ is then defined as the sound pattern of the phrases and sentences by the variation of pitch in the voice. Table 3.6 shows examples of such trade marks cases that posses phonetic similarity.

Table 3.6 Examples of phonetic similarity cases (OHIM, 2012c)

Earlier sign	Contested sign	Relevant territory	Case No
FEMARA	Femagro	EU	R 0722/2008-4
4US	for us	BX	R 0166/2010-1
HCOIL	HELI-COIL	DE	R 1071/2009-1 similar to a low degree

Purely figurative trade marks are not subject to phonetic assessment, as they do not have element that can be read. Thus, the phonetic assessment only limited to the following comparison cases:

1. Word mark with word mark.
2. Word mark with figurative word mark.
3. Figurative word mark with figurative word mark.

3.2 Conceptual Model

This section describes the conceptual model and the system framework of the proposed trade mark similarity assessment support system. It consists of two sub-sections namely the conceptual model description and the system architecture presentation. The proposed conceptual model advances the study in trade mark similarity and retrieval by utilising the three similarity aspects, i.e. the visual, conceptual and phonetic aspects in the trade mark similarity assessment model. The three aspects are incorporated in the model based on the current trade mark assessment practice which considers those similarity aspects.

3.2.1 Conceptual Model

The conceptual model of the trade mark similarity assessment system is shown in Figure 3.2. The model is built upon four main modules i.e. visual similarity, conceptual similarity, phonetic similarity and inference engine modules. Each module employs relatively different approach and technology. For example, in visual similarity module, content-based image retrieval (CBIR) technology is the major part that plays important role for visual comparison. The modules employs low-level feature, i.e. the shape features to derive visual descriptors for trade mark comparison.

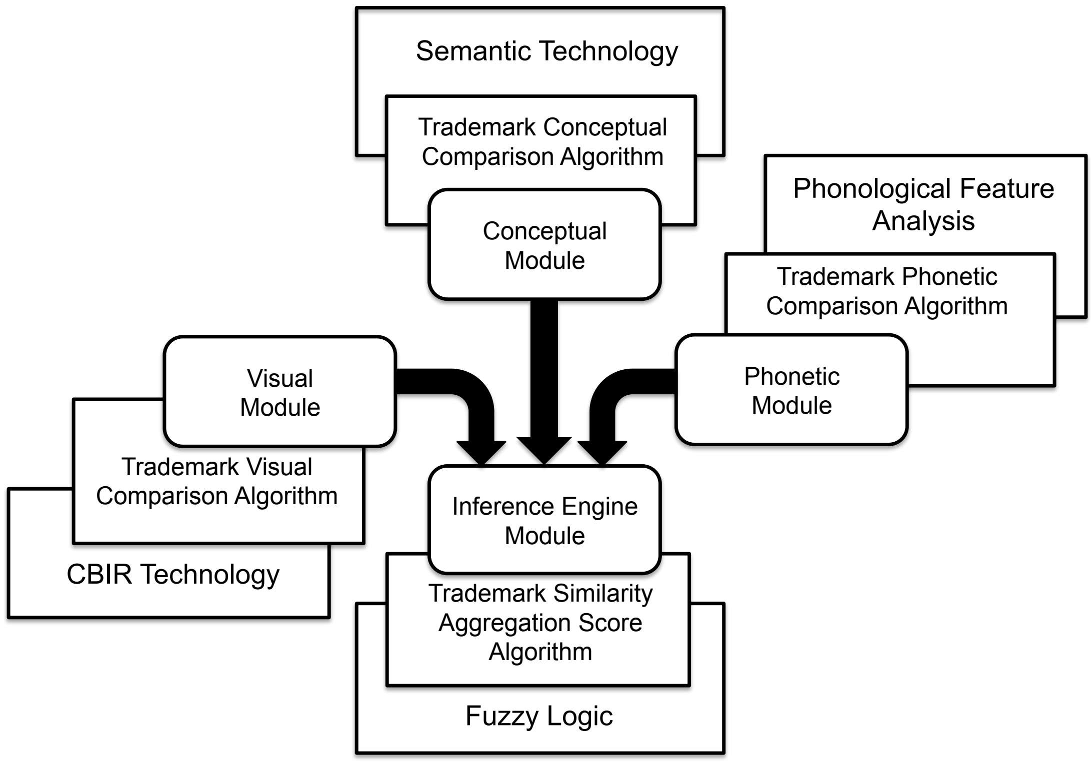


Figure 3.2 Trade mark similarity assessment conceptual model

The semantic aspect of trade mark similarity is examined and analysed in the conceptual similarity module. This module employs semantic technology, which enables the computation of the conceptual similarity between trade marks, with the utilisation of an external knowledge source in the form of a lexical ontology, together with natural language processing. The similarity score for the conceptual similarity is then derived based on the set similarity theory i.e. Tversky's contrast model. The phonetic aspect of trade mark similarity is then examined using phonemes analysis in the phonetic similarity module. The analysis compares each phoneme using their phonological features, which are extracted based on human speech articulation. The phonetic similarity score is then computed using these features. The trade mark phonetic comparison algorithm established in this module also provides a mechanism to compare the phonetic aspects of trade marks with typographic characters.

Inference engine module aggregates the overall similarity scores between trade marks based on the similarity scores produced from the previously mentioned modules. Conceptually, the output of the aggregation process performed by the inference engine should reflect the degree of overall similarity between the trade marks. The module is developed using a fuzzy-based inference that utilises fuzzy logic for the inference process.

The following section describes the framework of the conceptual model proposed in this chapter.

3.2.2 System Framework

Figure 3.3 shows a framework that comprehensively conceptualizes the trade mark similarity assessment support system proposed in this study. As can be seen from the figure, it consists of four main modules and a layered structure of the required tasks is also displayed in each module. Each of modules is designed based on its individual functionality, which requires different set of approaches and technology to perform their pre-defined functions. The framework also shows, how the individual similarity modules i.e. the visual, conceptual and phonetic modules are linked to the inference engine module for overall similarity assessment.

The visual similarity module performs trade mark similarity analysis based on their visual aspects. The modules generally consist of two parts: the part that examines the visual similarity aspects of pure figurative image and the part that examines the trade mark with text i.e. word mark and figurative word mark. The former part mainly employs CBIR technology that utilises low-level image feature i.e. the shape feature, for the similarity comparison analysis. Similar to any other retrieval system, the module is also designed to return trade marks based on their similarity ranking score. The later part in the module utilises an orthographic string

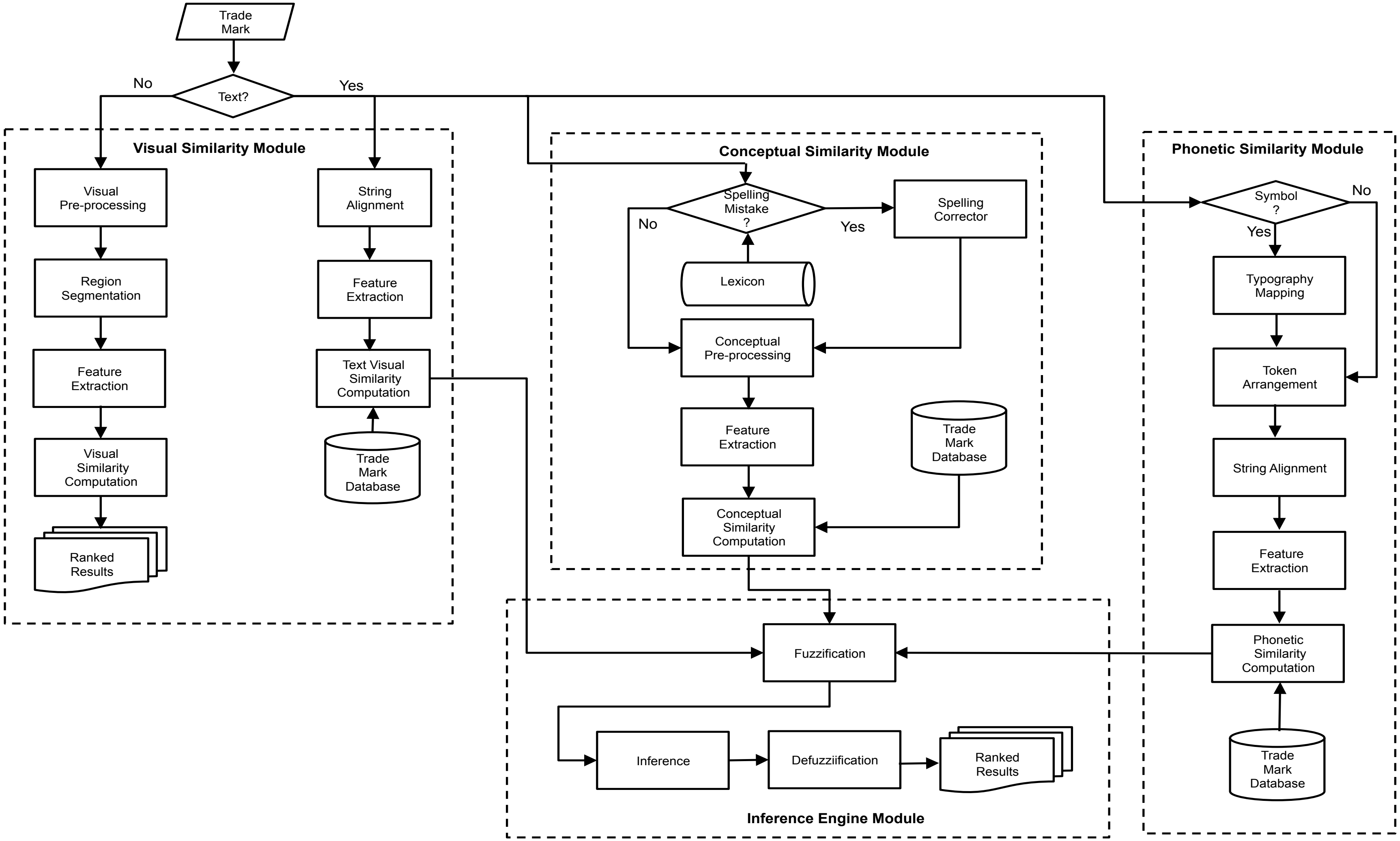


Figure 3.3 A framework of the proposed support system

similarity approach together with shape-based image feature comparison and analysis, as in the first part.

The second module, i.e. the conceptual module, examines and performs similarity comparison based on the semantic aspect of trade mark. The Natural language processing (NLP) methods are employed in this module to process the trade mark text data. The most crucial technology employed in this module is the semantic technology which helps bridge the gap between the trade mark text to their conceptual aspect. External knowledge sources in the form of lexicon and lexical ontology provide lexical meaning and platform, which enable the conceptual similarity computation. The work developed in this module provides a new computational approach in the domain of trade mark similarity and retrieval in which a revolutionary approach that examines the lexical meaning of trade mark is established.

Previous work in aural comparison involve with phonetic matching database of names. However, phonetic matching in trade mark offers additional challenges as it also involves text symbols i.e. '&', '@' etc., in the comparison process. This is because these symbols also acquire phonetic expressions i.e. 'n' and 'at' for the case of text symbols '&' and '@'. Secondly, these symbols can also carry more than one phonetic expression. For example, the text symbol '@' may be pronounced as 'at' when it appears at the beginning of a word but if it appears in the middle of a words it maybe pronounced or treated as a letter 'a'. The sound or phonetic aspect of trade mark is then examined using phonemes analysis and phonetic algorithm, which are employed in the phonetic similarity module. The trade mark phonetic similarity algorithm established in this module advances the state-of-art algorithm in this area, by providing a mechanism to compare the phonetic aspects of trade marks, in particular those with typography characters.

The main function of the inference engine module is to aggregate the overall trade mark degree of similarity as a function of the individual scores produced from the three similarity modules. It is a fuzzy-based inference system, which utilises the three aggregation tasks: the fuzzification, the inference and the defuzzification tasks. Fuzzy-based approach is employed in this study due to its remarkable performance in various engineering and non- engineering applications and furthermore the concept of fuzzy logic has long been recognised in legal related studies (Cook, 2001). A fuzzy rule-based system consists of a number of membership functions and a set of rules. Here, the set of fuzzy rules is derived based on the trade mark similarity examination manual and the empirical analysis performed on the actual trade mark dispute cases. Hence, this multiple input single output inference engine takes the output of the three similarity modules and performs aggregation process using a fuzzy inference model, specifically the Mamdani fuzzy inference model.

3.3 Summary

This chapter describes the three aspects of trade mark similarity i.e. the visual, conceptual and phonetic similarities, as outlined in the OHIM trade mark manual. A conceptual model of a trade mark similarity assessment support system is then introduced, which consists of four main modules. The model is based on content-based image retrieval technology, semantic technology, natural language processing and phonological-based analysis. A more comprehensive conceptualisation of the proposed model i.e. the trade mark similarity assessment support system framework, is also presented and discussed in this chapter.

Chapter 4

Trade Mark Assessment based on Visual Similarity

This chapter addresses the second objective of this study by proposing a trade mark retrieval algorithm, which employs an integrated shape feature descriptor and a feature matching strategy to visually compare and retrieve trade marks. The chapter is organised as follows: Section 4.1 describes the proposed shape-based trade mark retrieval algorithm for figurative trade marks. The section describes first the integrated shape feature descriptors and then the feature matching strategy. The next section then explains the experimental setup and evaluation performed on the proposed algorithm. The result of the experiment is also discussed in this section. Section 4.3 describes a trade mark visual comparison algorithm for trade marks with texts i.e. the word mark and figurative word mark. The algorithm uses the integrated shape feature descriptor in the proposed algorithm together with an optimal string alignment algorithm to perform the similarity comparison and analysis. Finally, Section 4.4 summarises this chapter.

4.1 The Proposed Visual Comparison and Retrieval Algorithm for Purely Figurative Trade Marks.

The proposed trade mark visual comparison and retrieval algorithm advances the previous study in trade mark image retrieval by utilising an integrated shape feature descriptor which has been able to capture the global and local characteristics/ properties of trade mark images. The local shape descriptor is employed in the algorithm to address the limitations of the global descriptors found in previous study. In addition, the algorithm also consists of a feature matching strategy to further improve the retrieval accuracy.

The proposed algorithm consists of two major stages. In the first stage, a developed integrated low-level shape-based feature descriptor is extracted to describe the trade mark images and in the following stage, a feature matching strategy based on the integrated descriptor is derived for similarity computation.

4.1.1 An Integrated Shape Features Descriptor Extraction

This section describes the integrated shape feature descriptors developed as part of the proposed retrieval algorithm. The integrated descriptor employs global and local low-level shape features to effectively describe the visual properties of trade mark images. The following sub-section briefly describes the computation of the Zernike Moment (ZM), which is the global feature employed. This is followed by a description of the local feature adapted in this descriptor, i.e. the edge-gradient co-occurrence matrix (EGCM).

Global shape feature

Zernike moment (ZM) is employed as part of the integrated shape feature descriptor based on the finding from previous research that has suggested a continuous orthogonal basis set for the calculation of image moments (Liao and Pawlak, 1998, Choraś, 2009) such as the one in ZM. The utilisation of the orthogonal moments aims to overcome problems encountered in invariant moments such as information redundancy and noise sensitivity. In ZM, each degree of moment in an image is unique and independent. In addition, the application of ZM as a shape feature does not require knowledge of shape boundary. This is also another advantage since not all images have clearly defined boundaries.

The theory of ZM is very similar to the Fourier descriptor (FD) as it is also a transform-based descriptor (Zhang and Lu, 2004). Furthermore, the set of ZM coefficients is also unique which make it applicable to represent the shape characteristics, especially those in the lower order, although it is possible for two different shapes to have some of the same moments. In ZM, the transformation of image information is from Cartesian to polar space but not in the spectral domain as it is in FD.

Mathematically, ZM are derived from the Zernike polynomials basis set, which is a complete set of complex-valued functions that are orthogonal on a unit disk. Zernike polynomials of order *n* with repetition *m* can be expressed in polar coordinates form as:

$$V_{nm}(x,y) = R_{nm}(r) \cdot e^{jm\theta} \tag{4.1}$$

where $r^2=x^2+y^2$,$j=\sqrt{-1}$, $\theta=tan^{-1}(y/x)$ (Lei et al., 2008a) and R_{nm} is the orthogonal radial polynomial defined as follows

$$R_{nm}(r) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!(\frac{n-2s+|m|}{2})!(\frac{n-2s-|m|}{2})} r^{n-2s} \tag{4.2}$$

Therefore, for an image function of *f(x,y),* ZM of order *n* with repetition *m* is given as:

$$Z_{nm} = \frac{n+1}{n} \sum_{x} \sum_{y} f(x,y) \cdot V_{nm}(x,y) \tag{4.3}$$

The magnitudes of ZM are naturally rotational invariants. In this study, the ZM computation is then made invariant towards scale and translation by projecting the images onto a unit circle of a fixed radius, as described in (Wei et al., 2009) and the square to circular mapping approach as in (Wee and Paramesran, 2007). The square to circular approach is utilised to ensure that all regions in the image are transformed to the radial polar space. For each image in the trade mark database, the global feature is represented by a set of 36 ZM coefficients up to the tenth order.

Local shape feature

The local feature employed in the proposed integrated descriptor is known as the edge gradient co-occurrence matrix (EGCM). The EGCM can be also regarded as a contour descriptor due to the fact that its computation is derived from the contour or edge information. The local characteristics are further expressed through the computation of the co-occurrence matrix, which suits the additional characteristics required as the second shape descriptor in this work.

The algorithm to extract the EGCM is largely motivated by the work in (Watanabe et al., 2010), which employs the co-occurrence matrix of the gradient orientation for the human detection descriptor. The first step in constructing the co-occurrence matrix is to obtain the gradient direction of each pixel. Thus, the gradient direction at the pixel location x and y, in the binary shape images I is defined as the following:

$$\Phi(x,y) = \tan^{-1}\frac{I(x+1,y)-I(x-1,y)}{I(x,y+1)-I(x,y-1)} \tag{4.4}$$

in which it considers the neighbouring pixels with respect to the pixel at location x and y. The angles are then quantised to eight gradient orientations. Figure 4.1 shows the eight gradient orientations employed in this computation. Using the equation (4.4), a relationship between two adjacent pixels is expressed and used to capture the local properties of the shape. More spatial relationships are then captured through the construction of an 8×8 co-occurrence matrix from the computed gradients.

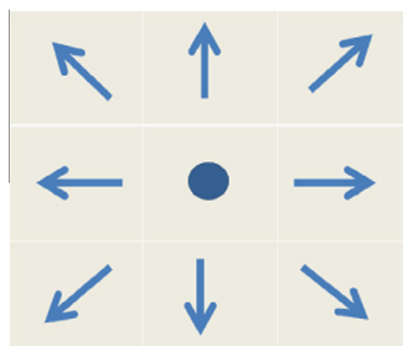


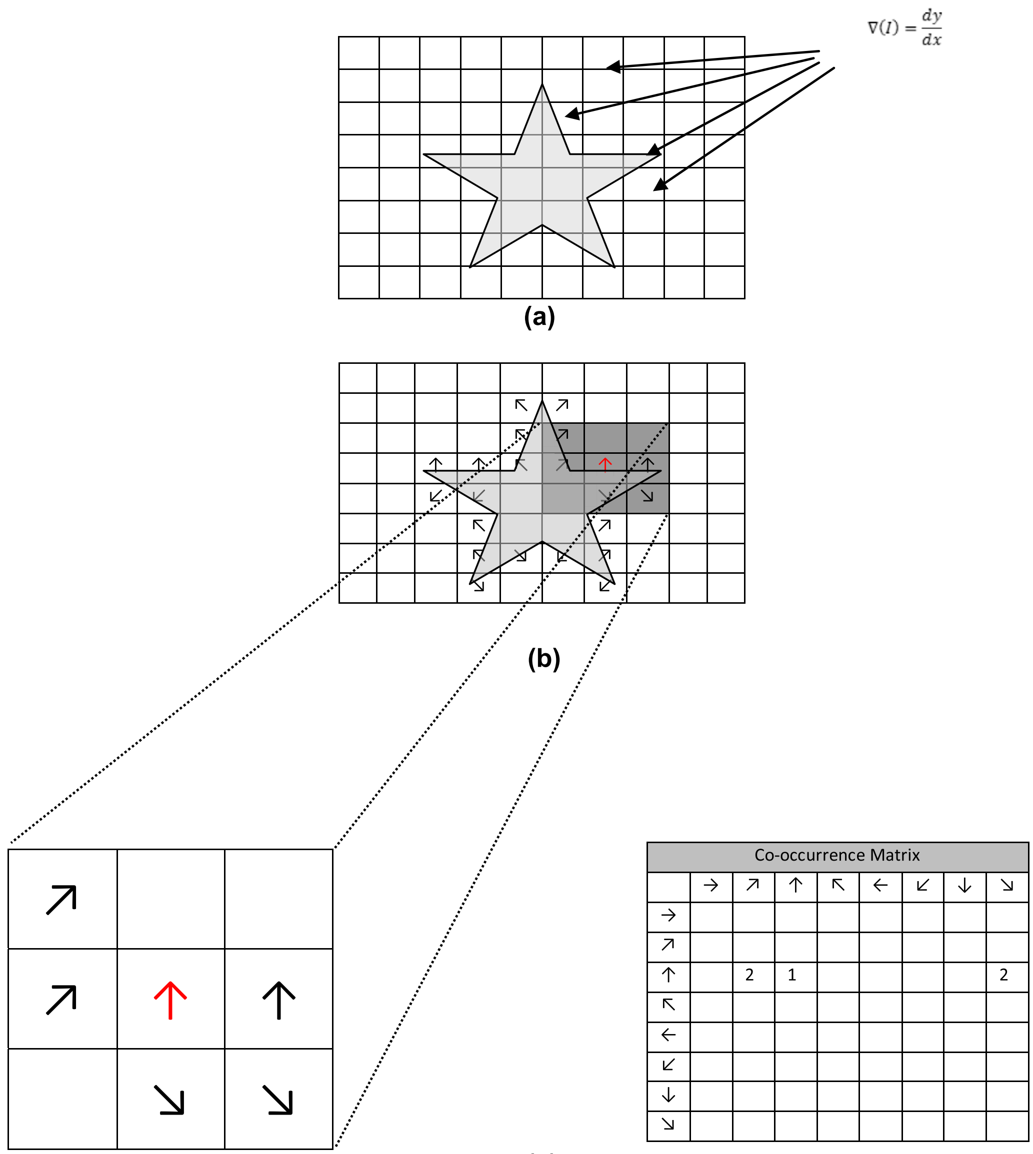
Figure 4.1 Eight gradient orientations

In CBIR applications, the co-occurrence matrix approach is widely applied in texture feature extraction algorithms due to its ability to describe the relative pixels relationship where the matrix is constructed using the grey level intensities of an image (Gonzalez and Woods, 2010). In the proposed local shape feature, the co-occurrence matrix employed here uses the gradients information described above as the raw data, when constructing the matrix. The rationale behind this implementation is to capture the neighbouring pixels' gradient information, which could represent the local properties of the shape in an image.

Since the co-occurrence matrix is not invariant under translation, scale and rotation, a few adjustments to the shape images are performed in the pre-processing stage. All images are initially cropped to a fixed size and the rotation of the images is adjusted by using the angle between the x-axis and the major axis of the images. This adjustment is supported by the Image Processing Toolbox available in Matlab. To further improve the computational time, only boundary pixels are used when generating the matrix. Figure 4.2 shows the pseudo code of the EGCM extraction algorithm which has been adapted from (Watanabe et al., 2010, Gonzalez, 2010) and an illustrative example of the EGCM derivation is shown in Figure 4.3.

```
Pseudocode: /*comment*/
/*This part of the code is performed for the EGCM extraction algorithm*/
define C, φ and S as the co-occurrence matrix, the gradiennt matrix and the 3 x 3 scanning window
define I as the input image
define K as the list of coordinates of the boundary pixels extracted using Canny operator
for all pixels in I,
    if the pixels coordinate is one of the coordinates in K,
        compute Eq. 4.4 and label the pixel with one of the eight orientations to update φ,
        else
        label the pixels as no gradient.
    end if
end for
for the coordinate location in K,
    run the scanning window S in φ to check the gradient of the eight neighbouring pixels,
    for each gradient pair found in S,
        update the co-occurrence matrix C,
    end for
end for
```

Figure 4.2 The pseudo code of the EGCM algorithm



	→	↗	↑	↖	←	↙	↓	↘
→								
↗								
↑		2	1					2
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Figure 4.3 An Illustrative example of the EGCM computation: (a) the gradient computation of each image pixels, (b) the gradient angle direction after quantisation to eight different directions, the empty cells correspond to the no gradient pixels (the background and foreground homogeneous region) and (c) an instantaneous example of the co-occurrence matrix construction using one of the contour pixels coloured in red. The matrix will be updated as the 3 x 3 window moves along the contour line.

Mathematically, the traditional co-occurrence matrix defined over an n x m size image with an offset of 1 (in horizontal direction) is given by the following equation:

$$C(p,q) = \sum_{x=1}^{n}\sum_{y=1}^{m}\begin{cases} 1, & \text{if} \quad \Phi(x,y) = p \quad \text{and} \quad \Phi(x+1,y) = q \\ 0, & \text{otherwise} \end{cases} \tag{4.5}$$

where *p* and *q* is the gradient direction and Φ is the gradient orientation image. However, since the construction of the co-occurrence matrix in this study is performed on the contour pixels and the co-occurrence pairs considered are the eight neighbouring cells, the mathematical expression can be further expressed as the following:

$$C(p,q) = \sum_{k=1}^{K}\sum_{s=1}^{8}\begin{cases} 1, & \text{if} \quad I(e(k)) = p \quad \text{and} \quad I(e(k)+d_s) = q \\ 0, & \text{otherwise} \end{cases} \tag{4.6}$$

where *e* is the coordinate of a contour of length *K* and δ_s is the distance of one pixel in the direction of the eight gradient orientations.

4.1.2 Feature Matching Stage

The main objective of this stage is to compute the similarity or dissimilarity values of images using the extracted integrated shape feature descriptor described in the previous sub-section. In this stage, a feature matching strategy is developed as it is particularly important in the retrieval systems that deal with multi features. Therefore, since the trade mark retrieval system proposed in this study utilises two shape features, it is necessary to develop a matching algorithm that will provide an optimum solution.

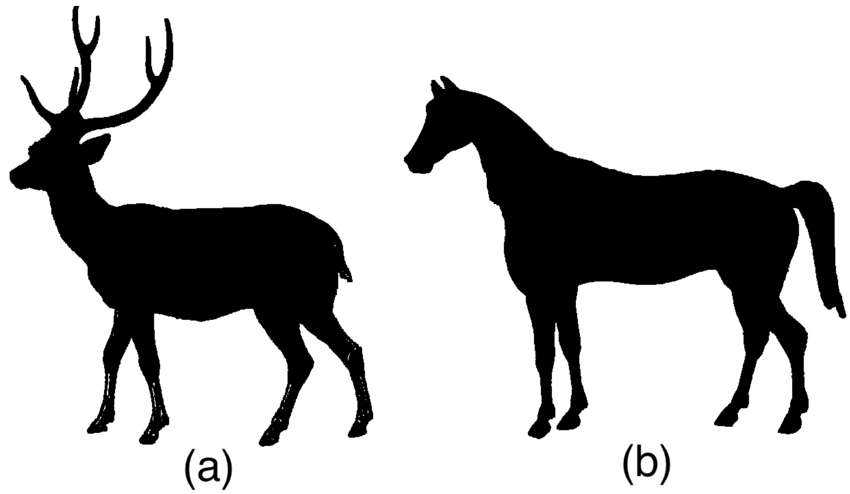


Figure 4.4 Images from deer and horse classes (Database-MPEG7-Shape)

Consider the image shown in Figure 4.4, which illustrates two images from the MPEG7 shape database that belong to different classes: ‘deer’ (Figure 4.4a) and ‘horse’ (Figure 4.4b). It should be noted that in general, both images are globally similar i.e. both animals have four legs and similar body shapes. The obvious differencesbetween (a) and (b) are the horns and tails. Combining the two shape features as one vector and computing the similarity by using a direct Euclidean distance of both features may not be the right approach to compare (a) and (b) because the global and local similarities of both images are different (i.e. small global similarity but large local similarity).

Suppose that image (a) is the query image, a good system would retrieve all images in class (a) followed by other similar images from other classes such as (b). Therefore, not only should the system be able to detect the detailed information that distinguishes (a) and (b) but it should be also capable of retrieving other similar images, assuming they exist in the database.

The proposed feature matching strategy is designed with the aim of enabling the system to retrieve images with both global and local similarities. The two commonly used feature matching algorithms are adapted here, namely the weight- based and two-component solution. In weight-based solutions such as the one reported in (Jain and Vailaya, 1998), the Euclidean distance metric is used to compute the similarity value of each feature. Different weights are then assigned to different feature vector components. In the two-component solution such as the one described in (Wei et al., 2009), the distance metric is used again to compute the similarity values for the two types of feature. For each feature, if the corresponding value is greater than the threshold value, a penalty is added to the current similarity value. In the end, the total similarity is the summation of the similarity values of the two features.

In the proposed feature matching strategy, the similarity values are computed before and after the filtering stage. In the first similarity computation, only the global features are employed. This filtering stage is essential to ensure that only images that are globally similar progress to the next stage. The similarity values are computed using the Euclidean distance metric as follows:

$$S(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{4.7}$$

where q is the ZM feature for the query image and p is the ZM feature for the p_{th} image in the database. An average global similarity value is then computed and set as the threshold value. All the images with a global similarity value S_g, higher than the threshold value are not further considered in the second stage matching.

The second stage matching computes the similarity values of the local feature, S_l. The total similarity value is the summation of S_g*w_g and S_l*w_l. For this study, the weighting values w_g and w_l , based on empirical evidence, are set at 0.2 and 0.8, respectively. Figure 4.5 and 4.6 show the stages involved and the flowchart of the proposed retrieval algorithm.

4.2 Experimental Setup and Evaluation

This section describes the experimental setup and the performance analysis conducted to evaluate the proposed retrieval algorithm. A trade mark retrieval system is built to test the performance of the proposed retrieval algorithm. The system consists of three main modules: input, query and retrieval modules. The input module is responsible for the offline feature extraction process on all the images in the database. The query module conducts the online feature extraction of the query images while the retrieval module performs the online matching process.

4.2.1 Experimental Setup

The evaluation of the proposed algorithm involves two experiments. The first experiment is to observe the performance of the proposed algorithm in terms of its retrieval capability and robustness in describing shape images; the second experiment is to test the proposed algorithm on a standard set of figurative trade mark database. The first experiment uses the shape database of the MPEG7 collection. This database is a standard database commonly used in shape-based image retrieval studies and has been also widely used in trade mark retrieval studies (Hong and Jiang, 2008, Wei et al., 2009). The database consists of 1,400 images that has been grouped into 70 classes. Since the trade mark retrieval system is based on shape features, the database is

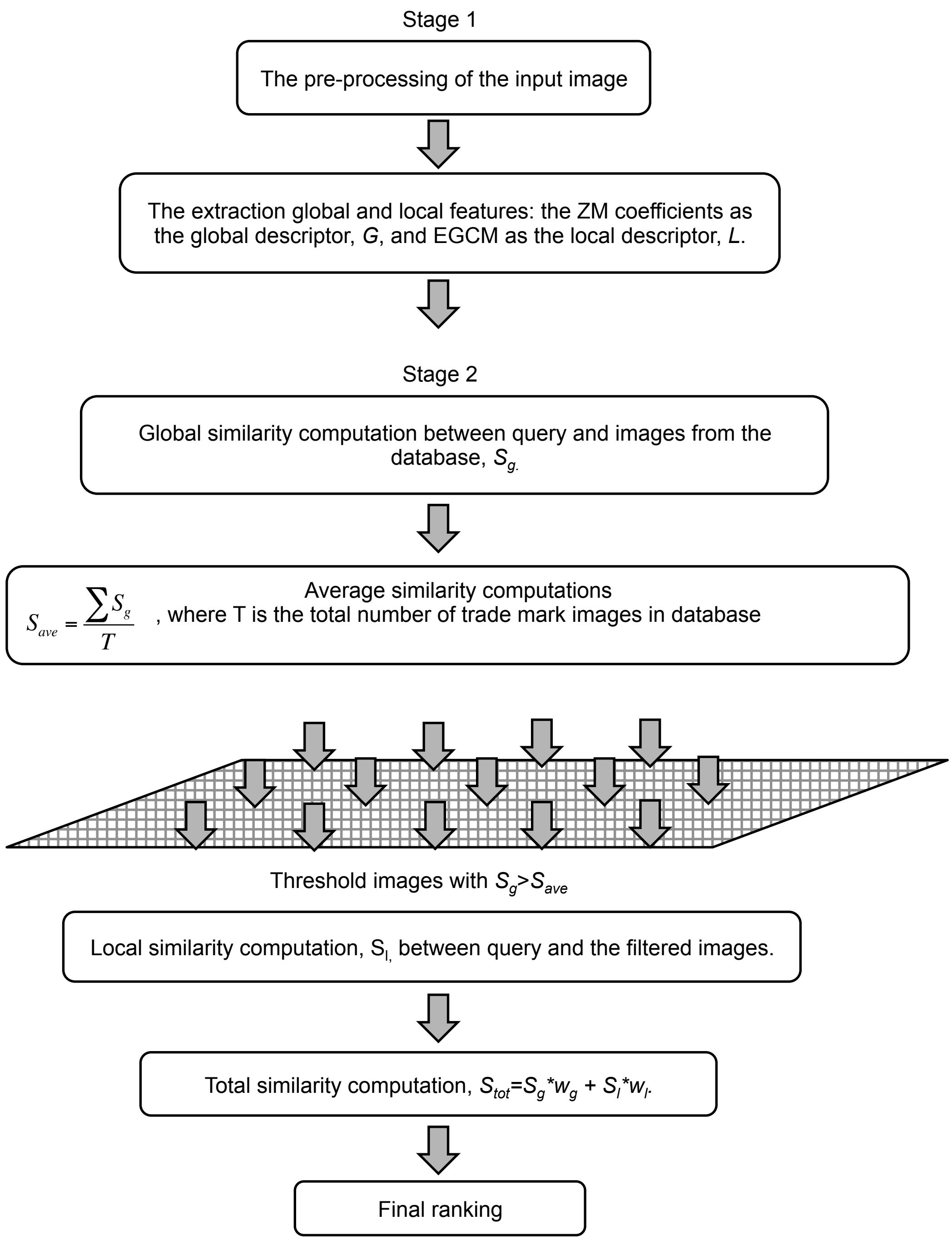


Figure 4.5 The stages of the proposed trade mark retrieval algorithm

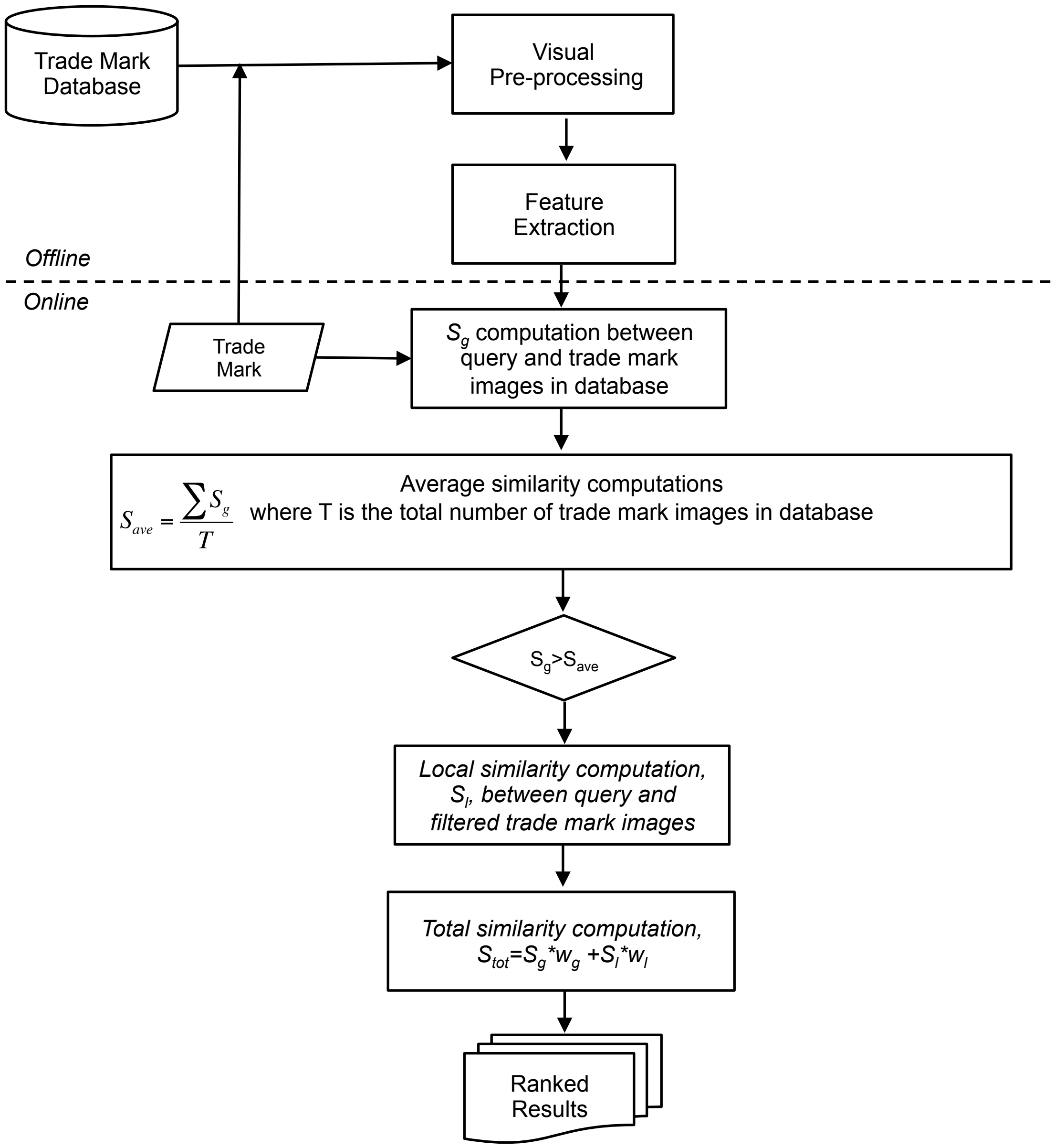


Figure 4.6 Flowchart of the proposed trade mark retrieval algorithm

highly relevant for this study. The precision and recall graph is used as the measure to show the performance of the proposed algorithm. This measure is one of the standard measures used for information retrieval evaluation in particular for dataset with equal number element in the relevant classes such as the MPEG-7 shape dataset. The second experiment employed the MPEG-7 trade mark database, which is also another standard database used in trade mark retrieval study. In this experiment, the Bull's eye score measure and the normalised modified retrieval rank measure are used as the performance measures. These are another standard information retrieval measure normally used for dataset with uneven number of element in the relevant classes such as the ones used in this experiment.

Experiment 1:

In this experiment, the accuracy of the system is analysed using a precision and recall graph, which is the standard performance measurement and the most commonly used assessment in CBIR research (Hong and Jiang, 2008, Wei et al., 2009, Qi et al., 2010, Di Ruberto and Morgera, 2008). The graph is plotted using the average precision when all 1,400 images in the database are used as the query image. The performance of the proposed shape feature is compared with other commonly used features previously i.e. the Hu moments, FD, wavelet descriptor, and ZM (Zhang and Lu, 2004, Zhang and Lu, 2003, Zhang and Lu, 2001). The performance of the proposed local feature (EGCM) is also included in this experiment to evaluate its individual performance before combining with the global shape feature ZM.

The proposed system is also tested using different distance metrics utilised in the feature matching algorithm i.e. Euclidean, normalised Euclidean, Manhattan, normalised Manhattan and cosine metrics. The main purpose of this analysis is to observe the influence of distance metrics on the retrieval performance of the proposed feature matching algorithm.

The normalised distance metrics are computed based on the distribution of the shape feature extracted. For each feature vector, the average (mean) is initially computed. The standard deviation of the entire computed mean is then generated. The value of this standard deviation is used to normalise the distance metric computation in which (4.6) is then divided by the computed standard deviation.

A qualitative analysis of the retrieved results is also performed by the means of visual inspections. In this analysis, two randomly selected images are used as query images and then the retrieval of the first twenty images is examined. The main objective of this analysis is to show the full extent of the improvement of the proposed algorithm because the precision/recall graph is based only on the retrieval of images that are of the same class as the query image. In other words, this analysis is performed to observe the capability of the proposed solution to retrieve images that resemble similarities to the query, even though they are not from the same class. The retrieval results for one of the images analysed in this study are also compared with the results reported in (Qi et al., 2010)

Experiment 2:

In the second experiment, the proposed shape features and the feature matching strategy are tested using the MPEG7 trade mark database (Database-MPEG7-TM). This database is also another standard database for trade mark retrieval and shape studies and has been previously used in (Zhang and Lu, 2003, Hung et al., 2006). The database consists of 3,600 binary trade mark images. Since the database does not provide pre-determined classes, the retrieval performance is measured based on the Bull's eye score and the normalised modified retrieval rank (NMRR) of the ten randomly selected trade marks. The Bull's eyes score is the retrieval score, measured based on the top *2xNG* retrieved images, where *NG* is the total number of relevant images in the database. The NMRR score ranges from 0 to 1, where 0 indicates a perfect retrieval.

4.2.2 Results and Analysis

Experiment 1:

Figure 4.7 shows the precision/recall graph of the proposed algorithm using ZM and EGCM as the shape features over some other well-known shape features i.e. ZM, Hu and FD. The graph shows that the proposed algorithm has surpassed the performance of other commonly used algorithms, producing an improvement of 5%, from the ZM precision/recall performance. It is also interesting to observe that the retrieval performance has increased by 136% from the EGCM algorithm, despite the poor performance of the EGCM on its own. This implies that, although the EGCM has not been able to capture the global properties of images, it is still useful and worth combining with a good global descriptor.

Figure 4.8 shows the results of a comparative study of different distance metrics. It can be observed from the graph that distance metrics have a relatively small influence on the performance of the retrieval system. Nevertheless, the normalised Euclidean metric provides the optimum performance, and this is followed by the Manhattan distance metrics with only a 0.9% difference.

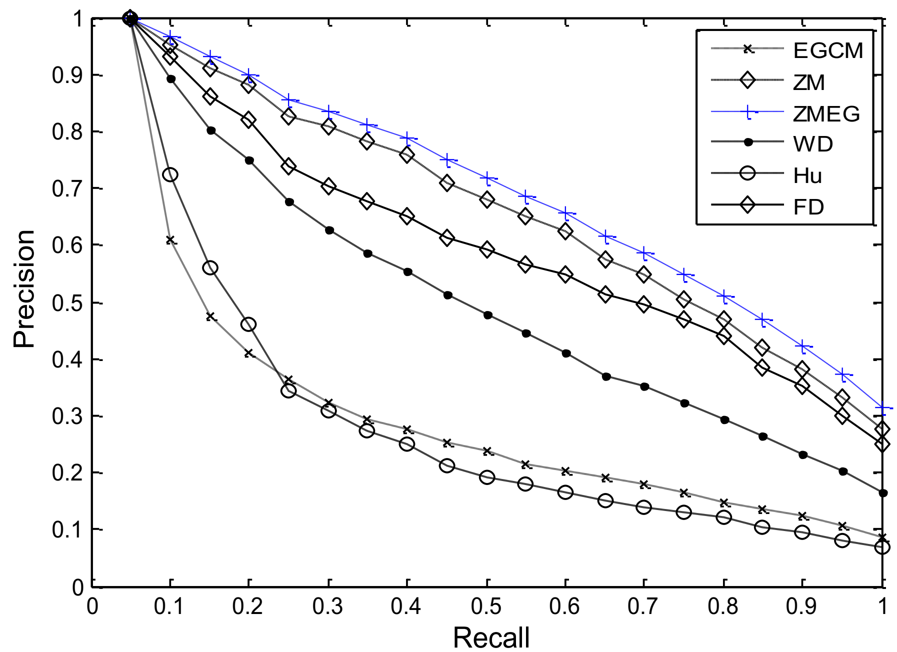


Figure 4.7 The precision/recall graph of EGCM, ZM, ZMEG, WD, Hu and FD

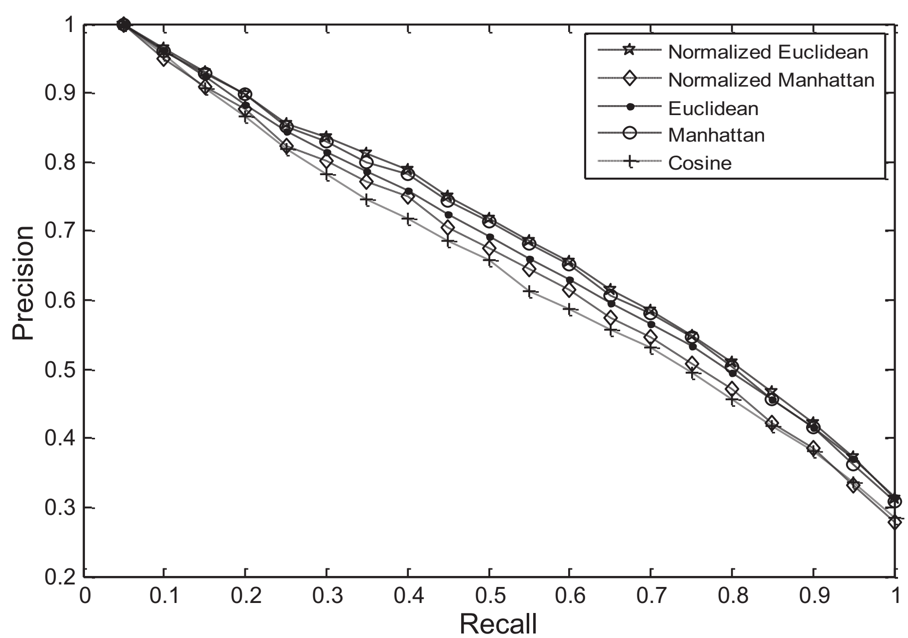


Figure 4.8 The precision/recall graph using normalised Euclidean, normalised Manhattan, Euclidean, Manhattan and cosine distance metrics

The MPEG7 database also consists of several classes, which are highly similar such as ‘horse.gif’ and ‘deer.gif’ classes. Here, the retrieval performance is also visually analysed using retrieval examples. It is found that images retrieved by the proposed algorithm are visually more similar compared to those retrieved by other algorithms, and that the algorithm is also able to retrieve similar images from other classes. Figure 4.9 and 4.10 show the retrieval results using the proposed algorithms, for the query of two images: ‘deer-5.gif’ and ‘fish-5.gif’. The visual observation shows that the proposed algorithm has been able to retrieve similar images belonging to different classes. For example, as shown in Figure 4.9, the retrieval for the query image ‘fish-5.gif’ has produced images from class ‘lmfish.gif’. Even for query image ‘deer-5.gif’, ZMEG has also been able to retrieve the images from class ‘horse.gif’, which are visually similar to the ‘deer.gif’ class.

The retrieval result from the proposed algorithm is also compared with the latest state of the art algorithm established just prior to this study. Thus, the retrieval results for the query image of ‘deer-5.gif’ from the MPEG7 shape database, are also compared with the illustrative results produced in (Qi et al., 2010) and (Wei et al., 2009), (see Figs. 4.11 and 4.12), and it has been observed that for that particular query image the proposed algorithm produces better results in terms of ranking and also retrieves more visually similar images despite the fact that they belong to different classes. For example, the retrieved results of the algorithm proposed by Wei et al. (2009) as shown by Qi et al. (2010), produced irrelevant retrieval results as shown in Figure 4.11 (see the images ranked as #5, 7–10), which resulted in only 50% correctly retrieved images

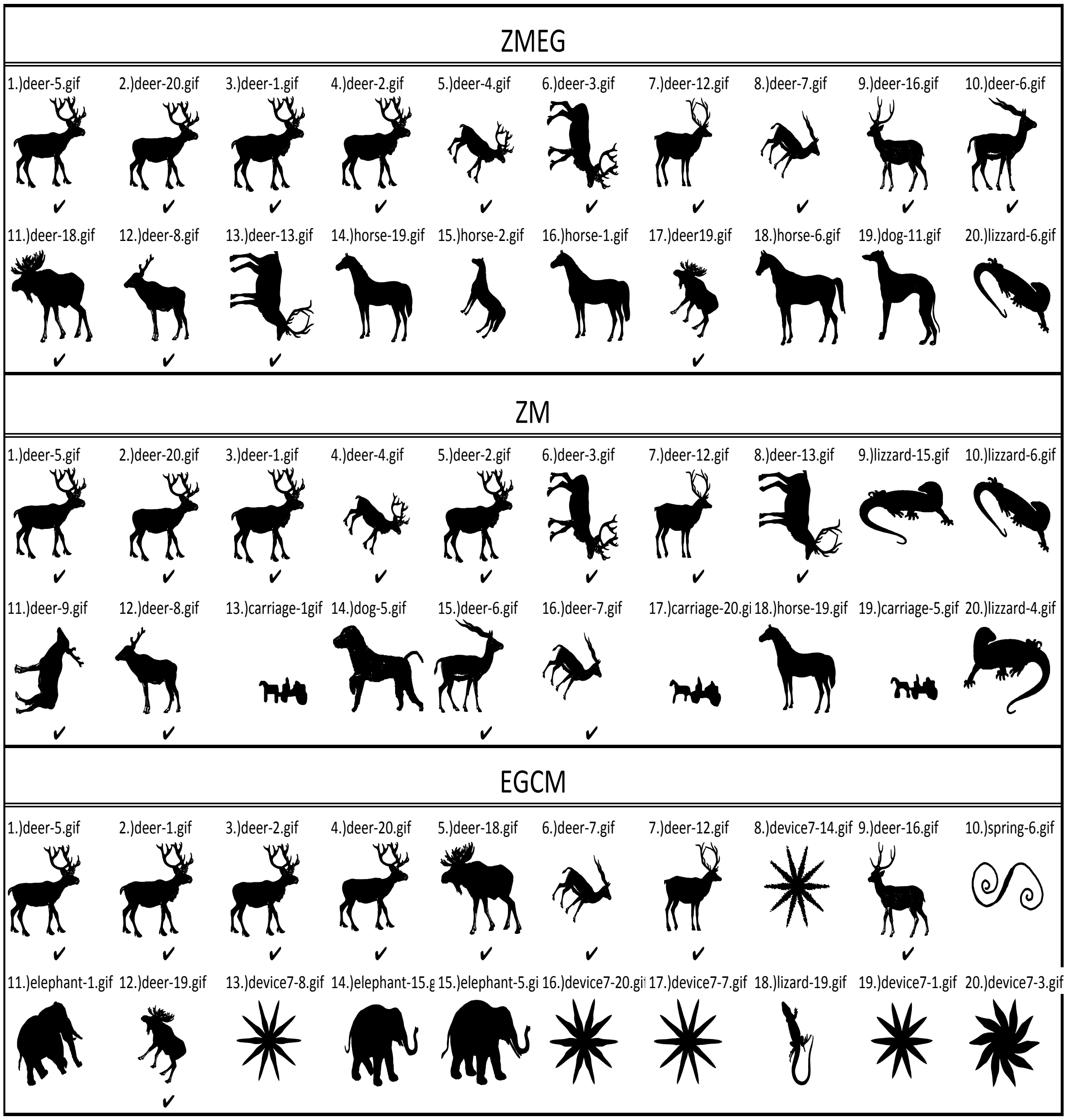


Figure 4.9 Retrieval results for ‘deer-5.gif’ used as a query image

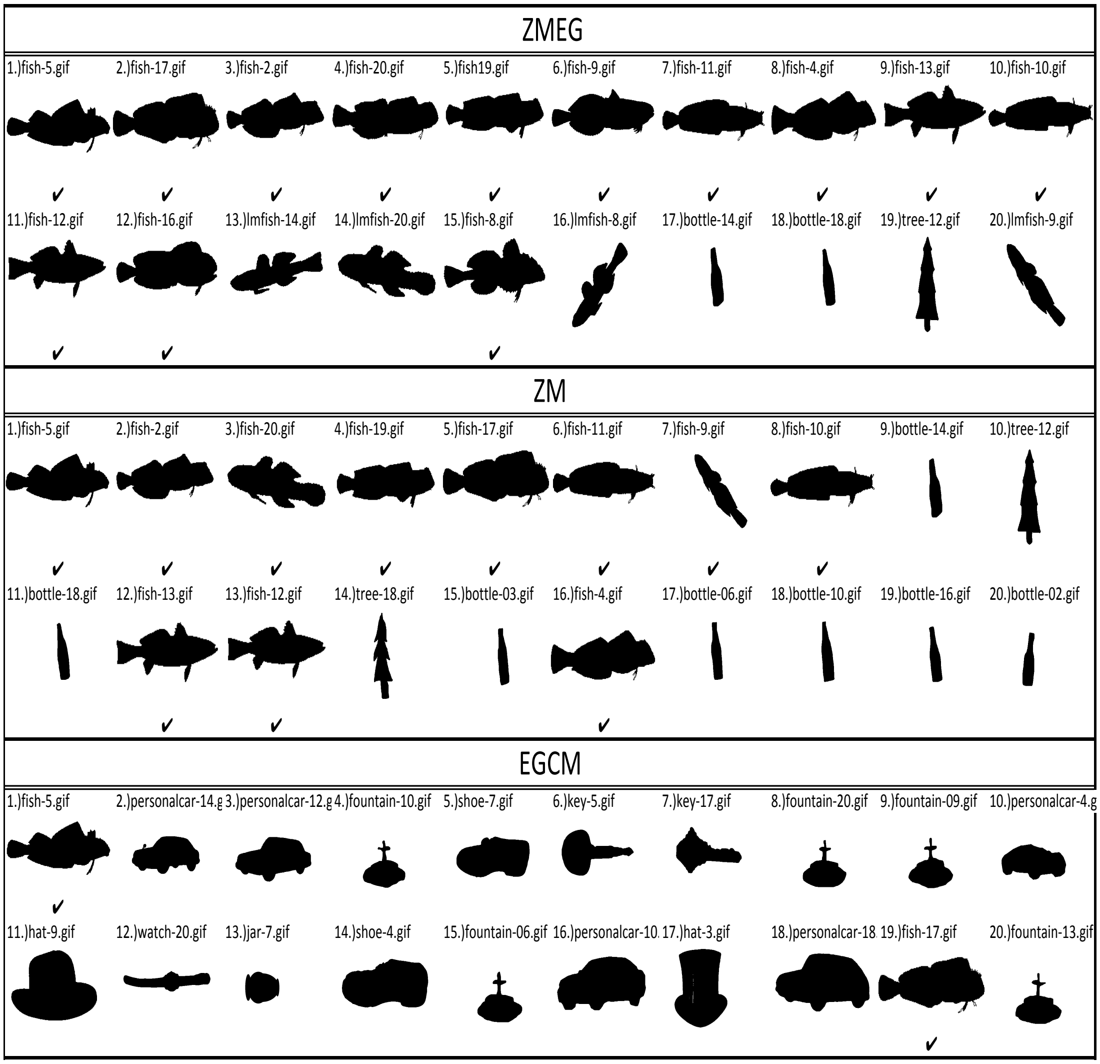


Figure 4.10 Retrieval results for ‘fish-5.gif’ used as query image

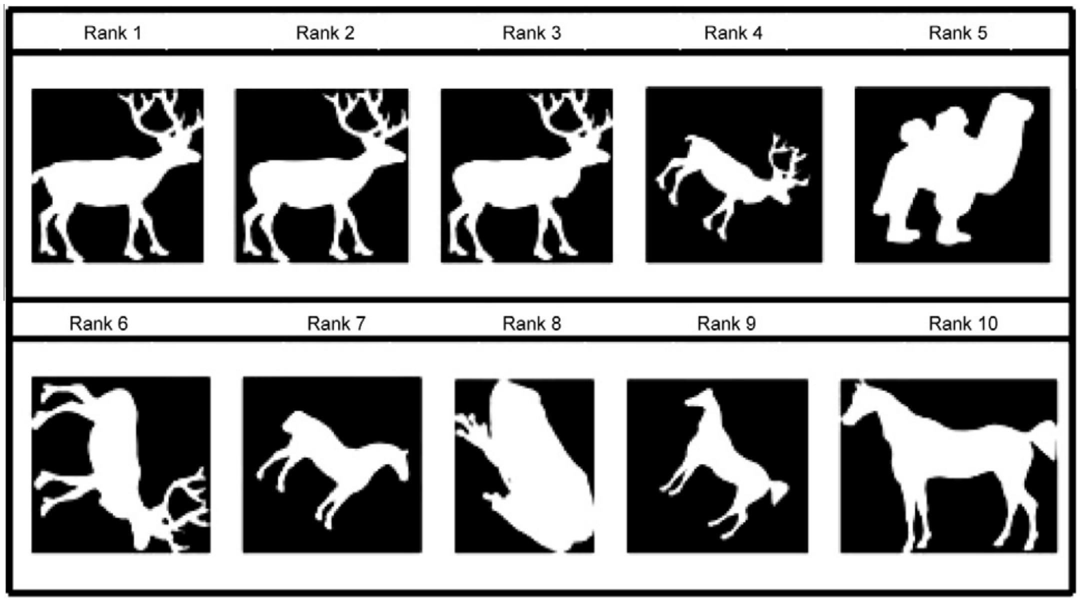


Figure 4.11 Retrieval results (Qi et al., 2010) using algorithm developed by Wei et al. (2009) for deer-5.gif' used as query image

in the first top 10 images. However, under a similar condition, the proposed algorithm has achieved 100% correctly retrieved images (see Figure 4.9). Results obtained from the algorithm by Qi et al. (2010), as shown in Figure 4.12, are also compared with the proposed algorithm and it has been observed that for that particular query image the proposed algorithm produces better results in terms of ranking and also retrieves more visually similar images despite the fact that they belong to different classes (see Figure 4.9 for the proposed algorithm retrieval results).

It is observed that for the proposed algorithm, the first thirteen retrieved images are correctly retrieved followed by another relevant retrieved image in the seventeenth rank, however, for the algorithm in Qi et al. (2010), although the first thirteen images are also correctly retrieved, the next relevant image is found in the eighteenth rank.

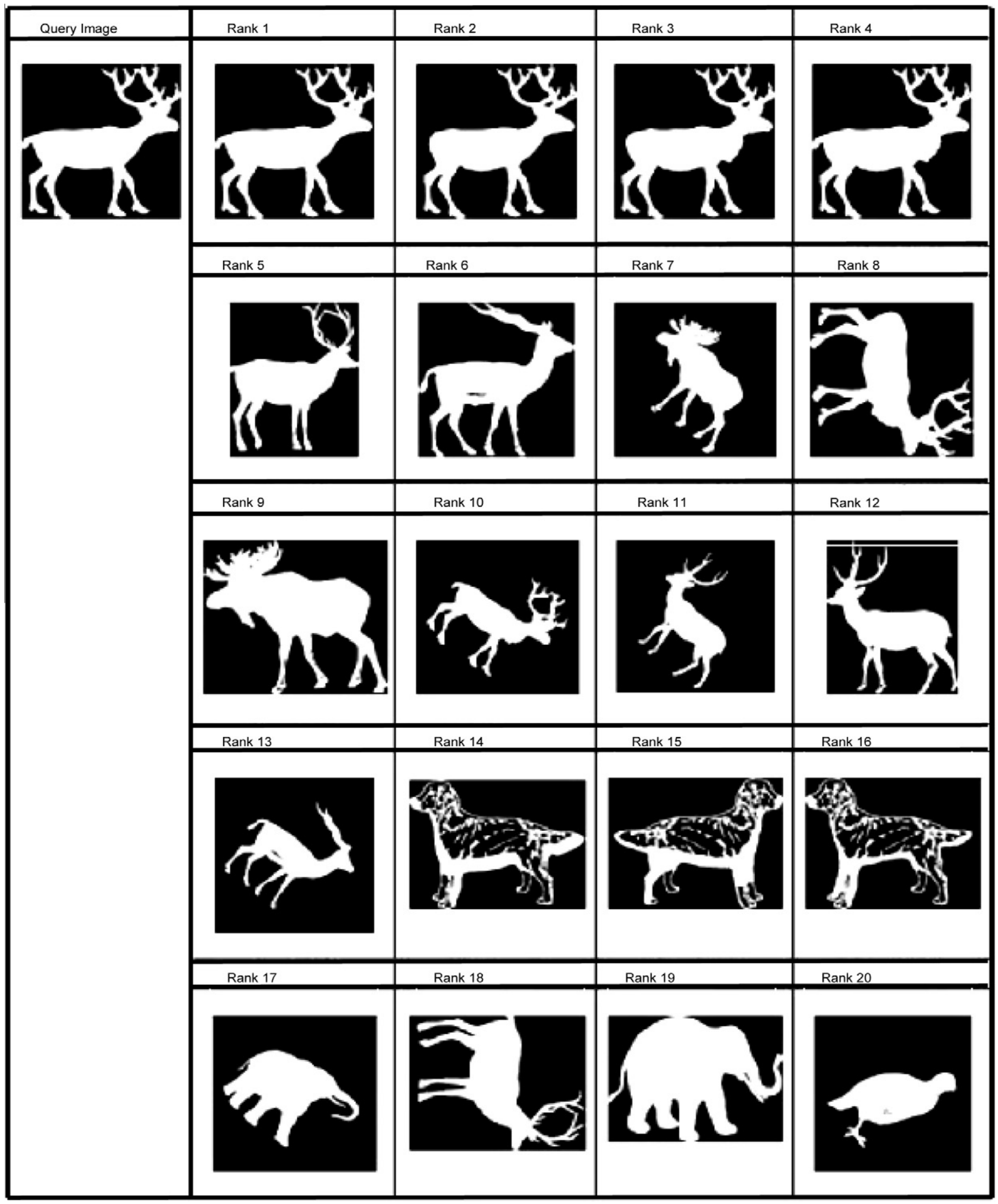


Figure 4.12 Retrieval results for 'deer-5.gif' used as query image using the algorithm proposed by Qi et al. (2010)

Experiment 2:

Table 4.1 shows the Bull's eye score performance and the NMMR score of the proposed shape feature and the conventional ZM using ten randomly selected images from the database. Generally, the Bull's eye score produces almost comparable results where ZMEG average score of the ten tested images exceeds the ZM score by 2.35%. However, in terms of the ranking capability, ZMEG provides a much better performance where the NMRR score improves by 19.8%. Therefore, in general ZMEG provides better performance than ZM.

Table 4.1 Precision and ranking score of 10 randomly selected trade marks from MPEG7 trade mark database using ZM and ZMEG

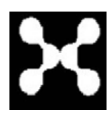
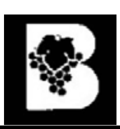
No	Query Images	Bull's eye score		NMRR		No	Query Images	Bull's eye score		NMRR	
		ZMEG	ZM	ZMEG	ZM			ZMEG	ZM	ZMEG	ZM
1		86%	71%	0.24	0.58	6		52%	48%	0.37	0.37
2		62%	62%	0.27	0.27	7		91%	91%	0.09	0.14
3		95%	95%	0.05	0.1	8		100%	100%	0	0
4		80%	80%	0.3	0.33	9		100%	100%	0.04	0
5		91%	91%	0.14	0.14	10		71%	71%	0.24	0.24

Figure 4.13 shows the retrieval results of the query image ‘945.jpg’ by using the proposed shape feature solution, the ZM and the EGCM. The ZMEG retrieval results provide a 75% precision rate for the top twenty retrievals; an improvement of 15% from the conventional ZM performance. The results also show that comparatively, ZMEG provides a better ranking performance for this image in which the first twelve retrieved images are correctly ranked and retrieved with the NMRR score of 0.24 (an improvement by 58.6% from the ZM score).

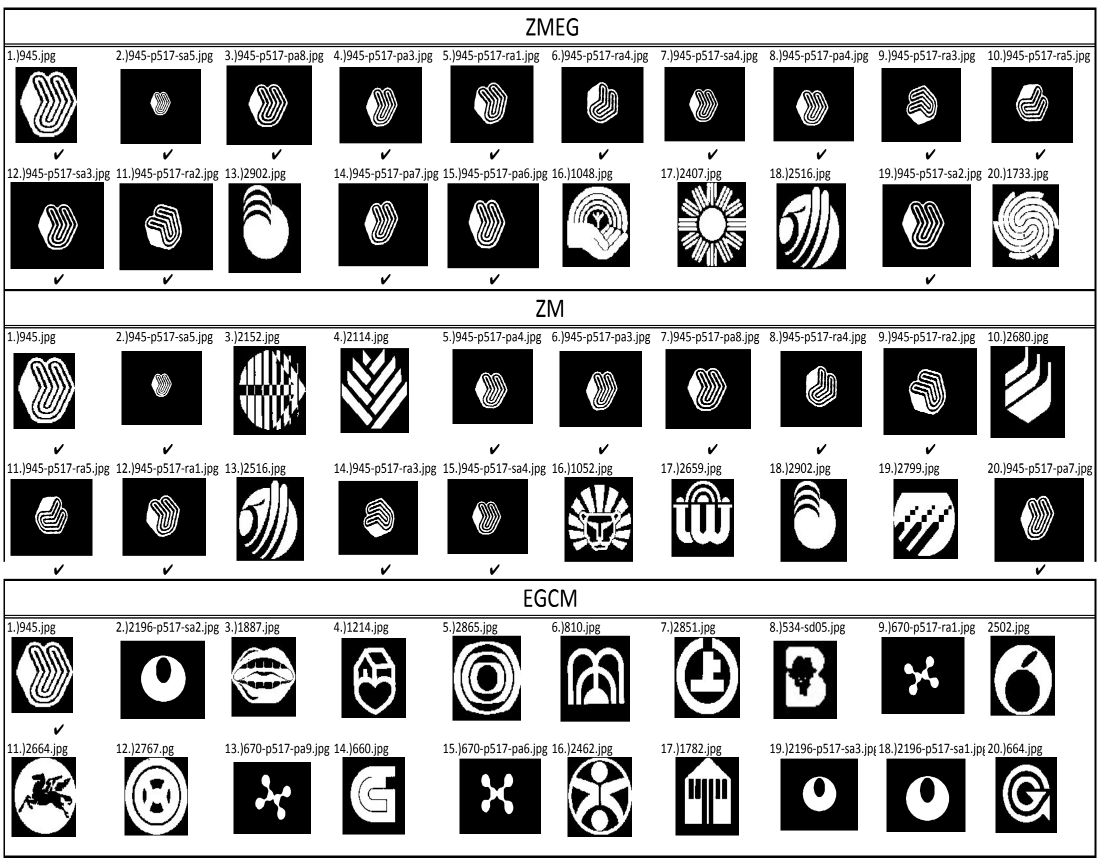


Figure 4.13 Retrieval results for ‘945.jpg’ used as query image

A similar analysis is performed using different distance metrics in order to analyse their influence on the retrieval performance of the system. The distance metrics tested here are the Euclidean, the normalised Euclidean, the Manhattan and the normalised Manhattan distance. Table 4.2 shows the performance of the proposed feature matching algorithm by using these distance metrics. The results show that the normalised Euclidean achieves the best Bull's eye and NMRR scores, with average scores of 82.8% and 0.174 consecutively. The normalised Euclidean metric has also significantly improved the Euclidean metrics performances in all ten tested images. The Manhattan and normalised Manhattan show a comparable performance in the Bull's eye score and also in the ranking score (NMRR), both with average scores of 79.6% and 0.275.

For the first and fourth query images, the normalised Euclidean produces the best results for both the Bull's eye score (86% for the first query image and 80% for the fourth query image) and the NMRR score (0.24 for the first query image and 0.3 for the fourth query image). For the third and seventh query images, the normalised Euclidean shows the best ranking scores (0.05 and 0.09) with similar Bull's eye scores to the Manhattan and the normalised Manhattan.

The choice of weighting values used has a secondary impact on the performance of the proposed retrieval algorithm. The weighting sets tested are *wg* = [0,0.1,...,0.9,1] and *wl* = [1,0.9,...,0.1,0]. It is observed that for the ten weighting parameter sets studied, the combination of *wg* = 0.2 and *wl* = 0.8 shows the best retrieval results. Figure 4.14 shows the retrieval results using different sets of weighting values for the query image '945.jpg'. From the figure, it can be concluded that the retrieval

Table 4.2 Precision and ranking performance of 10 randomly selected images from MPEG7 trade mark database using Manhattan, Euclidean, Normalised Manhattan and Normalised Euclidean metrics

No	Query Images	Bull's eye score				NMRR			
		Manhattan	Euclidean	Normalized Manhattan	Normalized Euclidean	Manhattan	Euclidean	Normalized Manhattan	Normalized Euclidean
1		76%	43%	76%	86%	0.43	0.62	0.43	0.24
2		62%	24%	62%	62%	0.27	0.54	0.27	0.27
3		95%	33%	95%	95%	0.58	0.61	0.58	0.05
4		62%	14%	62%	80%	0.58	0.61	0.58	0.3
5		91%	36%	91%	91%	0.14	0.43	0.14	0.14
6		52%	14%	52%	52%	0.37	0.61	0.37	0.37
7		91%	27%	91%	91%	0.14	0.43	0.14	0.09
8		100%	100%	100%	100%	0	0	0	0
9		100%	27%	100%	100%	0	0.43	0	0.04
10		67%	29%	67%	71%	0.24	0.58	0.24	0.24

Figure 4.14 Retrieval results using different weighting sets for ‘945.jpg’ used as query image

performance decreases as the weighting parameter wg increases and reaches the optimum performance when *wg* = 0.2 and *wl* = 0.8. Nevertheless, some images also exist which produce better results when using different *wg* and *wl* sets as shown in Figure 4.15. For the tested image '533.jpg', the combination of *wg* = 0.3 and *wl* = 0.7 provides a slightly better retrieval in terms of the ranking where the first irrelevant image is retrieved in the fifteenth rank.

In general, the results from both experiments show that the employed integrated shape descriptors employed in the proposed algorithm produced good retrieval results and therefore are applicable for trade mark type images. Hence, the integrated shape-based descriptor is further utilised for visual similarity comparison of trade mark with text i.e. word mark and figurative word mark, which will be described in the following section.

4.3 Visual Similarity Algorithm for Trade Marks with Texts

This section describes an algorithm employed in the course of this study to compare trade marks with texts-based on their visual similarity. The algorithm presented in this section employs the integrated shape feature descriptor developed in Section 4.1, which has been proven as good shape descriptor, to perform letter-to-letter visual comparison.

According to the OHIM trade mark manual, the most fundamental visual examination/analysis on trade mark with text element considers the number and also the sequence of the letters in the trade mark text. In normal text or words, this is referred to as orthographic similarity. In addition to that, the examination also considers

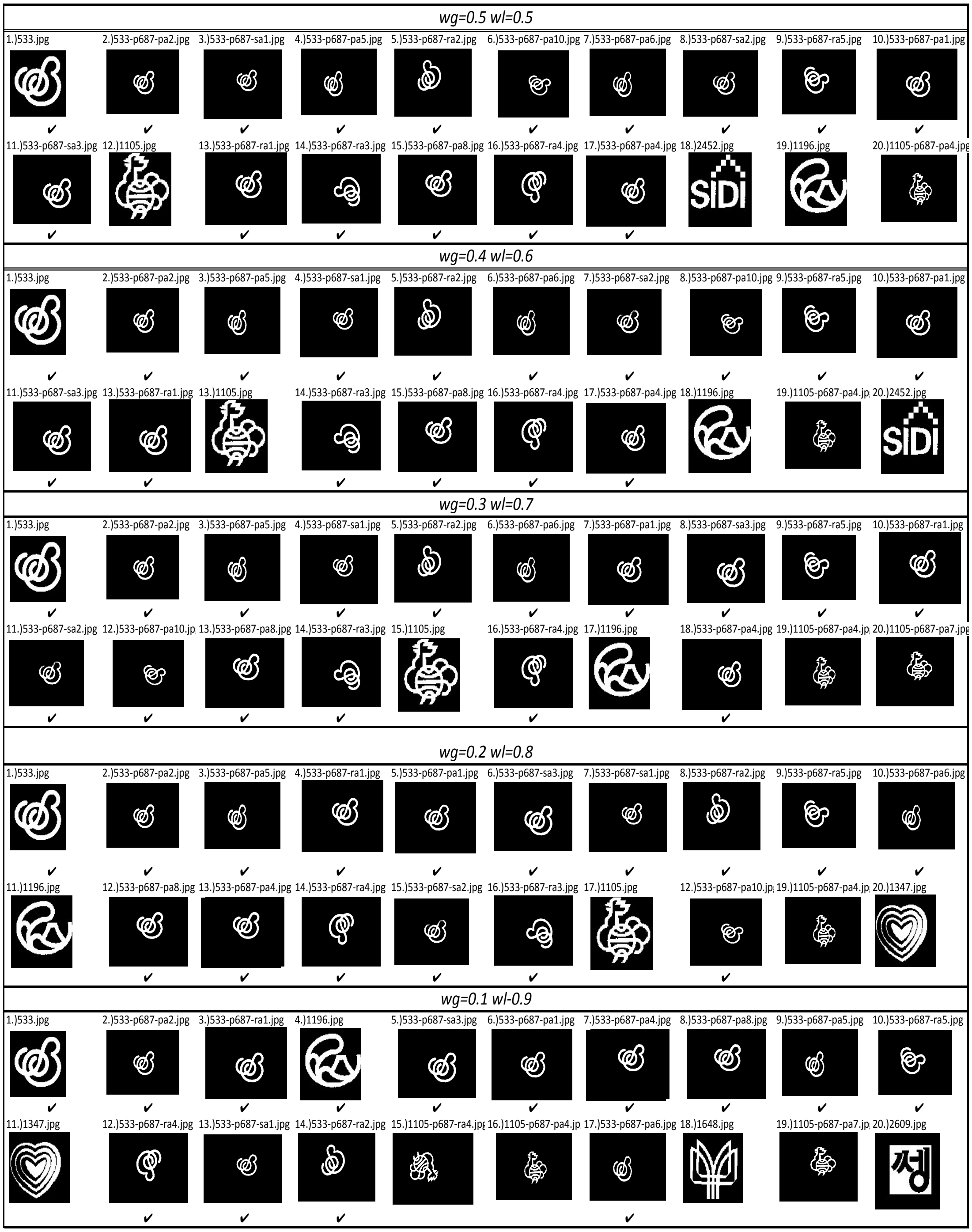


Figure 4.15 Retrieval results using different weighting sets for ‘533.jpg’ used as query image

the style of the letter used i.e. the typeface. Hence, the orthographic comparison of trade marks is further enhanced by utilising the shape descriptor described in the previous section as a means to describe the shape of the letters that form the trade mark text. The algorithm initially aligned two strings such that the alignment produces maximum number of aligned identical letters. Shape-based descriptor is then derived for each letters and pairwise letter comparison is computed based on the obtained descriptors. In the most commonly used orthographic-based string similarity algorithm, i.e. the approximate string matching algorithm, the similarity score between two strings is computed based on the minimum number of insertion, deletion, and substitution operations to make them identical strings. For example, the approximate string matching score between word marks “1NDEX” and “INDEX” is 1, which results in a normalised similarity score of 0.8 (1–[1/5]). However, a similar score will also be produced for a trade mark pair “1NDEX” and “XNDEX”, although in general the trade mark pair “1NDEX” and INDEX” appears to be more similar compared to the trade mark pair “1NDEX” and “XNDEX” and therefore should produce a different similarity score. This is due to the substitution operation in the approximate string matching algorithm that penalizes all non-matching letters with a score of 1, regardless of their visual similarity. A solution to this problem would be to compute the visual similarity between the aligned individual letters in the first and in the second trade mark, i.e. between “1” and “X”, between “N” and “N” and etc.

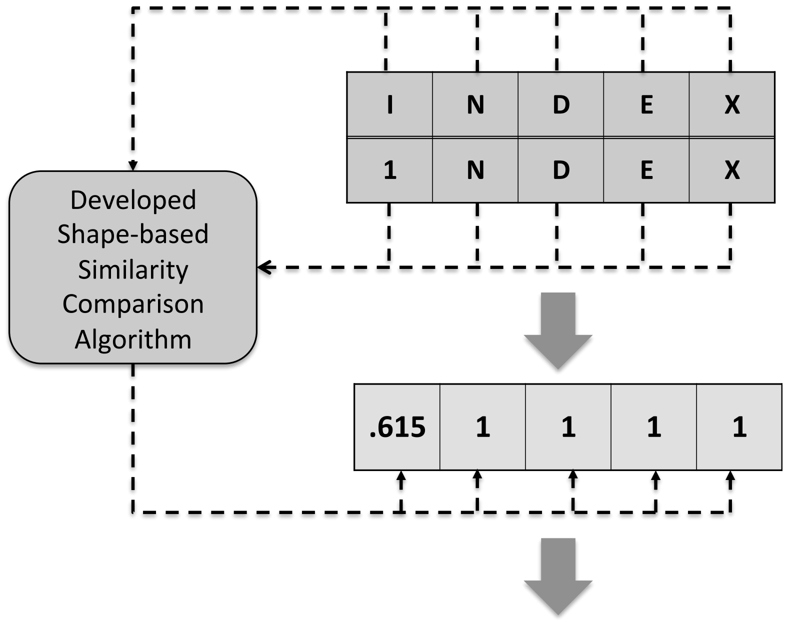
A pseudocode describing the visual similarity comparison score for such trade marks is shown in Table 4.3, and an illustrative example of the visual similarity comparison score computation used in this study is shown in Fig. 5. Two trade mark strings are first aligned using a cost matrix constructed based on an approach used in the approximate string matching algorithm (Navarro, 2001). The cost matrix provides information on the substitution, insertion and deletion position, which can also be used for constructing the alignment between two strings. Once, the alignment is established, letter-to-letter visual similarity comparison is performed using the shape descriptors as developed for the comparison of figurative marks.

Unlike in approximate string matching computation i.e. the edit distance, that penalizes the letter-to-letter comparison with either 1 or 0 values, such as “1” and “l” in the previous example that acquire a substitution penalty score of 1, the employed algorithm computes visual similarity between the letters using their visual feature, i.e. the shape descriptors. This approach provides a mechanism that can differentiate

Table 4.3 The pseudo code of the visual similarity score computation employed in the proposed algorithm

Pseudocode: /*comment*/

```
/* This part of the code is performed for the visual similarity
        score computation for trademark with text*/
define Qt and Dt as the query and trademark from the database
compute Aq and Ad as new strings that produce optimal alignment between Qt and Dt
define score as the letter-to-letter visual similarity matrix between Qt and Dt;
define m=max(length(Aq), length(Ad));
for i=0 until m
        if Aq(i)=Null || Ad(i)==Null
            score(i)=0;
        else
    score(i)=compute visual similarity score between Aq(i) and Ad(i)
 end
define total_score= sum(score)/m;
```



$$Sim = 4.615 / 5 = 0.923$$

Figure 4.16 An illustrative example of the visual similarity score computation employed in the proposed algorithm

between different letters and numbers that look similar, such as “1” and “I”, and less similar letters and numbers, such as “1” and “X”. In this study, the visual similarity computation for letter-to-letter comparison in trade mark text, is computed using the previously developed shape-based descriptor, which has been published in (Mohd Anuar et al., 2013).

Table 4.4 displays similarity scores, computed using both the approximate string matching algorithm and the employed visual similarity comparison algorithm to exhibit the differences and thus justify the approach undertaken in this visual comparison. The approximate string matching algorithm produced similar scores for both pairs, although the trade mark pair “1NDEX” and “INDEX” is more similar. This is due to the approach employed in the approximate string matching that penalizes the non-identical letters

Table 4.4 Visual similarity scores using approximate string matching and the proposed visual similarity score computation

	Approximate String Matching	Visual Similarity Score Computation on Trade mark Text
1NDEX :: INDEX	0.80	0.923
1NDEX :: XNDEX	0.80	0.861

with a binary penalty. However, by using the proposed visual similarity score computation algorithm, the visual similarity of trade mark pair “1NDEX and INDEX” produces a higher similarity score in comparison with the other pair, i.e., “1NDEX’ and “XNDEX”. This result is due to the approach considered in the computation, which uses the low-level shape-based visual feature of the letters that comprises the trade mark text for comparison.

4.4 Summary

This chapter addresses the second objective of this study by proposing an algorithm to compare and retrieve trade mark based on their visual aspects. For figurative trade marks, it is performed using a newly developed integrated shape feature descriptor and a feature matching strategy. The descriptors consist of the Zernike moments as the global descriptor and the edge-gradient co-occurrence matrix as the local descriptor. The proposed algorithm demonstrates an improved performance over state of the art algorithms for trade mark image retrieval.

The performance of the proposed algorithm is assessed using two standard databases: the MPEG7 shape database and the MPEG7 trade mark database. The performance measurement used in this study is the precision/ recall graph, the Bull’s eye score, the normalised modified retrieval rank and visual inspection analysis. The experiments also show that for the MPEG7 shape database, the precision/recall graph performance using the proposed algorithm outperforms several commonly used algorithms which utilise ZM, FD and Hu moments as descriptors. In the case of the trade mark MPEG7 database, the visual inspection of randomly selected images also shows good improvement results in comparison with the Bull's eye and the NMMR.

For trade marks with texts, the visual comparison is performed using the integrated shape feature descriptor together with an optimal string alignment algorithm. The algorithm is then compared with the approximate string algorithm i.e. a commonly used algorithm for string comparison, via visual inspection. It is found that the algorithm is able to differentiate between more similar and less similar trade mark text.

Chapter 5

Trade Mark Assessment based on Conceptual Similarity

The work presented in this chapter is motivated by the realisation that, despite the number of infringement cases that arises based on conceptual similarities, work to address this issue is still limited. It is also motivated by the understanding that trade mark similarity, one of the factors that contributes to the likelihood of confusion, may be linked to the semantics of the trade marks, i.e. their lexical meaning.

Hence, this chapter addresses the third objective of this study by proposing an algorithm that retrieves and compares trade marks based on their conceptual similarity. The scope of work in this chapter is trade marks with textual element i.e. word marks and figurative word marks. The chapter is organised as follows: Section 5.1 discusses the development of the proposed algorithm, which involves the database analysis and the conceptual model formulation. Section 5.2 describes the proposed algorithm. The experimental evaluation of the proposed algorithm is then explained in Section 5.3 and Section 5.4 summarises this chapter.

5.1 Database Analysis and Conceptual Model Formulation

The development of the proposed retrieval algorithm involves two stages. This section describes the first stage of the development i.e. the database analysis and the conceptual model formulation.

5.1.1 Database Acquisition and Analysis

The database employed in this study is built using a list of European trade mark infringement court cases from 1999 until 2012 (Database-Court-Cases). It consists of 700 trade mark disputed cases with visual, conceptual and phonetic similarities. The database is then analysed as a preliminary study for the development of the retrieval algorithm. The findings from the analysis show that the cases obtained can be divided into four groups. The first group, i.e. real words, corresponds to cases involving trade mark words derived from the lexical dictionary. 'Out of vocabulary' refers to trade marks with invented words, which do not have a lexical meaning. Trade marks with a combination of real and invented words are included in the 'mixture' group. The group 'other' contains trade marks with alphabetical text and family names.

The next portion of analysis concentrates on the 'real words' group, which covers about 37% of the database. The analysis of this group of trade marks is performed in order to understand the nature of the conceptual similarities arising from those cases. The analysis on the dispute cases shows that the trade marks can be further divided in four categories based on the type of similarities: exact match similarities, synonyms/antonyms, lexical conceptual relations and cross-lingual synonyms. Table 5.1 shows examples of each of these categories, and their distribution is shown in Figure 5.1.

Table 5.1 Four types of conceptual similarities

Disputed Trademarks	Similarity Type
ON DEMAND vs on Demand	Exact Match
fast clean vs Quiclean	Synonyms/Antonyms
MAGIC HOURS vs MAGIC TIMES	Lexical Relations
SHARK vs **Hai**	Foreign Mark

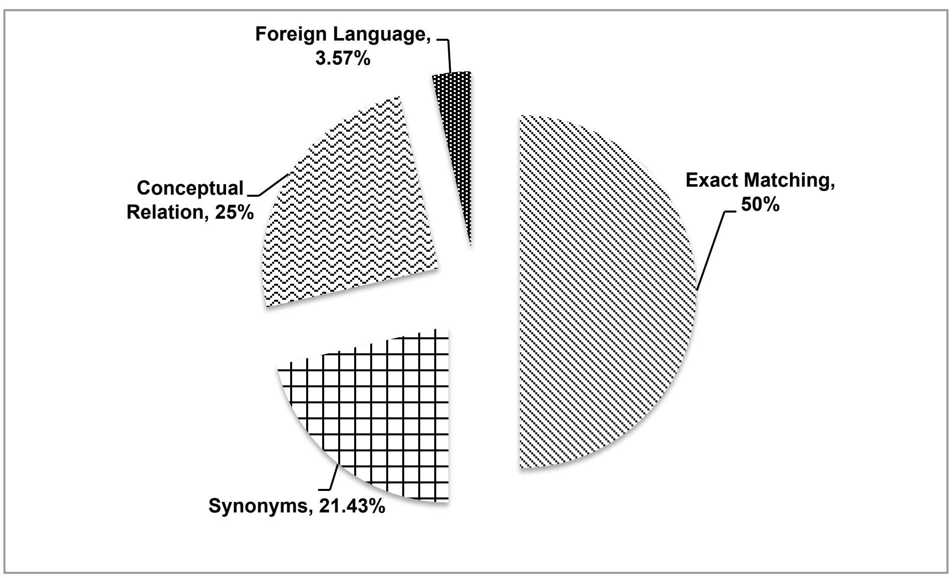


Figure 5.1 The distribution of the types of conceptual similarity of the database used

The exact match category is the simplest form of conceptual similarity, which can be identified easily using string matching frequently employed in keyword-based retrievals. The second category: synonyms and antonyms, requires external knowledge sources i.e. a dictionary or a thesaurus to extract the synonyms and antonyms of trade mark terms. The third category i.e. lexical and conceptual relations, also requires external knowledge sources together with a lexical ontology to compute the semantic similarity. The foreign language category requires a multilingual dictionary to translate the terms in the system semantic space (e.g. English) before further extraction of synonyms and antonyms. A summary of the main requirements for each category is shown in Table 5.2.

The distribution of the four categories, as shown in Figure 5.2, suggests that the similarity of 50% of the trade marks (i.e. those in synonyms/antonyms, lexical relations and foreign trade mark names categories) cannot be efficiently addressed by a

Table 5.2 Summary of the requirement for each category

Type of Conceptual Similarity	**Requirement**
Exact Match	String Matching
Synonyms/Antonyms	Dictionaries/Thesauri
Lexical Relations	Dictionaries/Thesauri and Lexical Ontology
Foreign Mark	Multilingual Dictionaries

traditional keyword-based search currently employed by trade mark registration offices. For example, the Boolean search for a trade mark i.e. MAGIC HOURS may recall a conceptually similar trade mark i.e. MAGIC TIMES, but will also retrieve a very long list of other trade marks that contain these two words as well as parts of the two strings, which still requires a substantial and tedious effort.

5.1.2 Conceptual Model

Based on the analysis performed on the actual trade mark infringement cases together with the guidelines provided in the trade mark manual, a conceptual model of a trade mark retrieval system is then developed. The conceptual model of the retrieval system is shown in Figure 5.2. The model consists of three main components namely

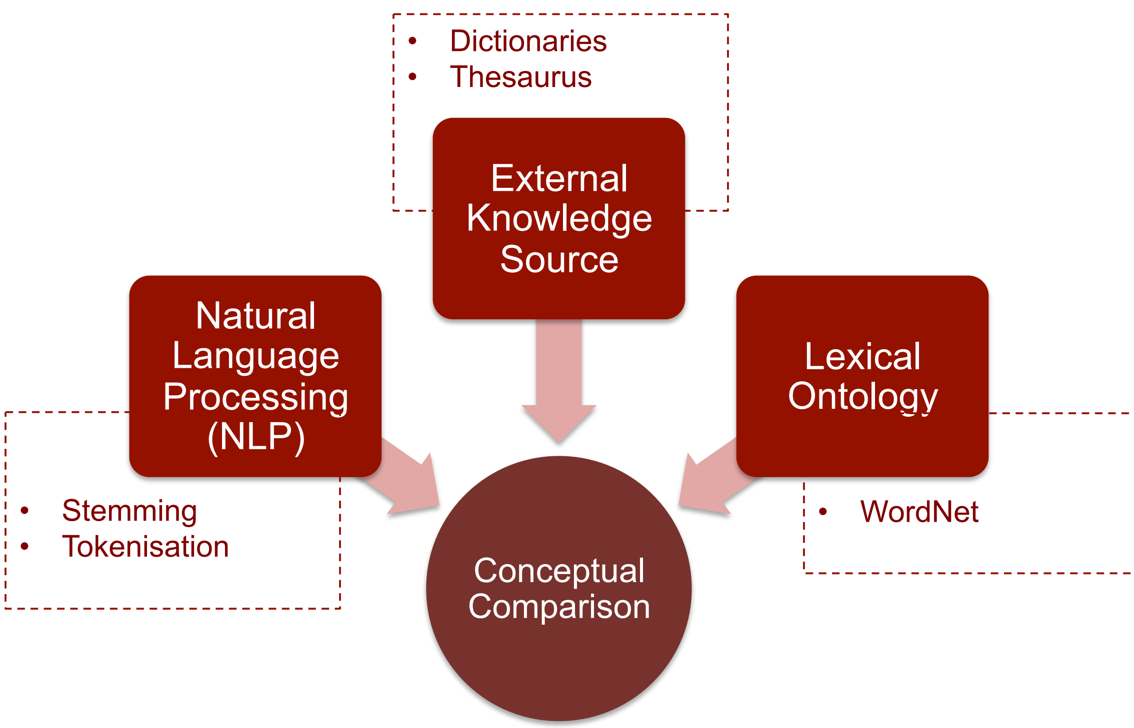


Figure 5.2 The conceptual model of the proposed algorithm.

the natural language processing (NLP), the external knowledge sources and a lexical ontology.

Trade mark text exists in various form i.e. single word, phrases and etc. Thus, basic NLP technique is required to perform text pre-processing such as *tokenisation* process which extracts the trade mark words in the form of tokens i.e. the 'MAGIC TIMES' trade mark will have two tokens i.e. 'magic' and 'times', and *stemming* which converts tokens into their root form.

The second component i.e. the external knowledge sources, serve as a linkage that map the trade mark text to their lexical meaning. They can be in the form of dictionaries, encyclopaedias or any form of lexicons. The link is highly essential, since the nature of conceptual similarity examination is based on the lexical meaning that arises between trade marks. This in line with the current practice of the trade mark examiner which refers to dictionaries/encyclopaedias when examining conceptual relations between trade marks.

Finally, lexical ontology is employed in this conceptual model as a mechanism to compute lexical distance between words/lexical entries. From the point of view of ontologies representation, a lexical ontology forms structural frameworks for organising lexical information such as in lexicons, which provide underlying lexical relationship for knowledge representation and organisation (Storey et al., 1998). For example, a lexical ontology contains lexical knowledge source relationships between its entries, as described by lexicons. The fine organisation structure of ontologies has therefore provided a foundation for many word similarity measures computations.

5.2 The Proposed Comparison and Retrieval Algorithm based on Conceptual Similarity.

Trade mark comparison based on conceptual similarity is a relatively new area in information retrieval (IR). The proposed algorithm advances the study in trade mark similarity research by providing a mechanism to compute the similarity between trade marks based on their conceptual similarity. This is based on the current practice of trade mark similarity examination that also considers the conceptual aspect of trade mark. The algorithm employs semantic technology in the form of an external knowledge source as a means to link the trade mark texts to their lexical meaning.

Hence, the proposed algorithm is developed based on semantic technology, which employs a lexical knowledge source to compare and thus retrieve trade marks based on their conceptual similarity. The conceptual model introduced in the previous section provides a bird's eye view of trade mark retrieval algorithm, which is based on their conceptual similarities. This part of the chapter will discuss the proposed retrieval algorithm developed based on the model. The algorithm in particular, will focus on the feature extraction process, the indexing process in the feature database and the similarity computation process during the retrieval. Altogether, the algorithm employs NLP techniques and the word similarity distance method, derived from the WordNet ontology, together with a new trade mark comparison measure. WordNet is employed in this algorithm due to its lexical relations that mirror human semantic organisation and has also been proven successful in many previously developed works. The trade mark similarity comparison measure is derived from the Tversky contrast model, a model well-known amongst theories of similarity (Amos, 1977).

Generally, the proposed algorithm involves three main processes: the feature extraction, the hash indexing and the trade mark similarity comparison measure. The feature extraction and the hash indexing are predominantly performed off-line for indexing purposes, while the similarity computation is performed online. The pseudo code presented in Figure 5.3 shows the steps involved in the proposed algorithm that looks for similar trade mark pairs in database.

1. Extracting features for trade mark representation in the algorithm.

Each trade mark is represented with two kinds of features. The first feature is the token set, which is extracted during the pre-processing process. Tokens from the trade marks

Pseudocode: /*comment*/

```
/* This part of the code is performed for the feature
        extraction and indexing part of the algorithm*/
define f_t as the token set of  a trademark;
define f_s as a set of of synonyms list that correspond
to the token set;
define f_t_all as a list of unique token extracted from the
database;
for each trademark in the database, do
  { extract f_t;
    extract f_s;
    for each token in f_t;
    { if(token does not exist in f_t_all);
          {update token into f_t_all;}}}
define hash_table as hash index table that maps token
to all trademarks in the database that contain simillar
token;
for each token in f_t_all;
  { find trademark that has similar token;
    update the hash_table;}
/*This part of code is performed during retrieval*/
for each trademark query
  { extract f_t and f_s for the query;
    map the f_s of the query to hash_table to get a list
    of trademark from the database;
    for each trademark in the extracted list from the
    hash_table
      {compute the conceptual similarity distance
    between the query and the trademark in the list}};
```

Figure 5.3 The pseudo code of the proposed retrieval algorithm are used as on of the feature sets due to the trade marks composition that normally involved multiple words. They are sets of English root words. For example, the word ‘flying’ will be converted to ‘fly’. The second feature is defined as the synonym set of the tokens and is extracted from the WordNet database. The synonym set defined in the context of this algorithm includes the synonyms, the direct hypernyms and the direct hyponyms of the corresponding tokens. Essentially, the outcome of this step yields two features: the token set and the synonym set. These are then stored to enable indexing.

2. Trade mark indexing using the hashing technique.

To reduce the computational time during the retrieval process, the features are indexed using a hashing technique. The indexing in the feature database is designed based on all the trade mark tokens existing in the database. Suppose there is a total of X unique tokens in the database, the hash table will then contain X number of rows. Each row then points to a list of trade marks which contain similar tokens. The final indexing table is merely a table that points to a collection of tokens i.e. a set of trade marks from the database that share similar tokens. In this manner, the distance computation is not conducted on the whole database, which therefore enhances the speed of the retrieval process. During the online search, the trade mark query features f_s, i.e. the synonyms set, are then mapped to a set of trade marks through a mapping function. This will therefore allow the trade mark similarity computation only on the set of trade marks that consist of at least one of the terms in f_s, i.e. the synonyms set belonging to the trade mark query.

3. Trade mark distance computation.

A trade mark distance computation measure is developed in this study and it is based on the similarity concept introduced in the Tversky contrast theory (Amos, 1977) . In this theory, Tversky defines the similarity between two objects as a function of unique and shared information about the object. Motivated by this idea, the similarity equation between a trade mark query, Q, and a trade mark, T, is derived as follows:

$$\begin{aligned} &\mathrm{sim}(Q,T) = \frac{|Q_{f_t} \cap T_{f_t}|}{|Q_{f_t} \cup T_{f_t}|} + \frac{|Q_{f_s} \cap T_{f_t}|}{D} + \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\max(\mathrm{word\_sim}(x_i, y_j))}{|Q_{f_t} \setminus T_{f_t}| \cdot |T_{f_t} \setminus Q_{f_t}|} \\ &x \in \{Q_{f_t} \setminus T_{f_t}\} \\ &y \in \{T_{f_t} \setminus Q_{f_t}\} \end{aligned} \tag{5.1}$$

where Q_{f_t} and Q_{f_s} are the token set and the synonyms set of the query, $\boldsymbol{T_{f_t}}$ is the token set of one of the trade marks from the database, $D = \max(|Q_{f_t}|, |T_{f_t}|)$, $Q_{f_t} \setminus T_{f_t}$ and $T_{f_t} \setminus Q_{f_t}$ is the relative complement set of T_{f_t} in Q_{f_t} and vice versa, having *i* and *j* numbers of set elements, and *word_sim* is the word similarity measure. The *word_sim* is not specific for one particular word similarity measure, instead Equation (5.1) is made generic for any word similarity measures depending on the need and usability. The proposed equation takes the value between 0 and 3 (0 being the lowest and 3 being the highest similarity). In this work several commonly used word similarity measures, which are derived based on WordNet ontology are considered and tested.

Figure 5.4 illustrates the three steps of the algorithm, using an example from a real court case involving ‘Red Bull’ and Figure 5.5 shows the trade mark similarity computation for this case.

5.3 Experimental Setup and Evaluation

This section describes the experimental setup and the evaluation method employed to evaluate the proposed retrieval algorithm. The algorithm is tested on two databases. Two experiments are then conducted to evaluate the performance of the proposed

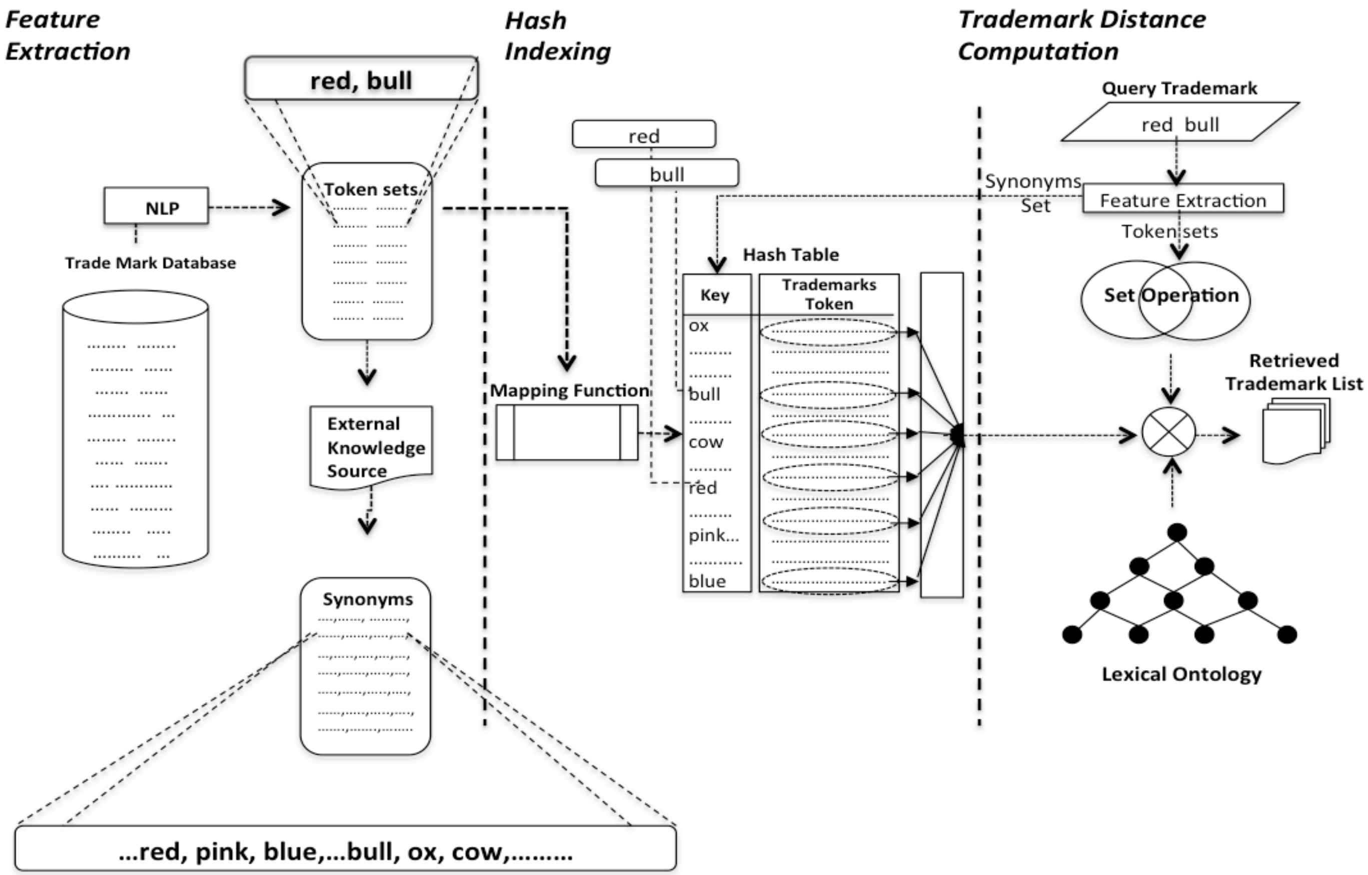


Figure 5.4 An illustrative example of the steps involved for one of the trade marks from real court case database: ‘Red Bull’

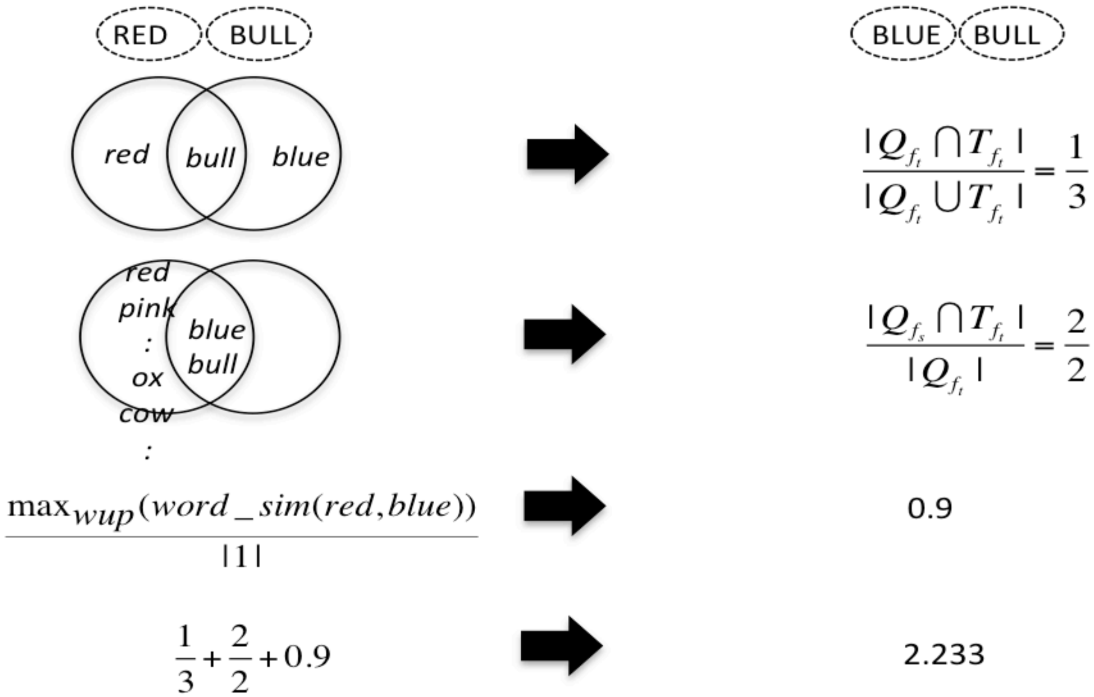


Figure 5.5 An illustrative example of trade mark similarity computation between ‘Red Bull’ as the query and ‘BlueBull’ from the real court case database

algorithm. The first evaluation is conducted using an information retrieval measure (i.e. the R-precision score), and the second evaluation is conducted through an open call task (i.e. crowdsourcing).

5.3.1 Experiment 1 Setup and Evaluation

Experimental Setup:

The objectives of this experiment are twofold. First, the experiment examines the feasibility of the proposed algorithm against the baseline algorithm (i.e. approximate string matching using edit distance) using the R-precision score measure. The measure is employed in this experiment based on the database used in this study i.e. the trade mark dispute cases database which contains 700 trade marks pairs. Thus the R-precision measures the precision score of the the top ranked retrieval results. Second, it investigates the effect of employing different word similarity measures i.e. the Wu & Palmer (Wu and Palmer, 1994), Resnik (Resnik, 1995), Lin(Lin, 1998), Jiang & Conrath (Jiang and Conrath, 1997), Leacock & Chodorow (Leacock and Chodorow, 1998) and Lesk (Banerjee and Pedersen, 2002) word measures. The outcome of this study may also suggest the most suitable word measure to be used in the trade mark retrieval algorithm.

Table 5.3 lists the 110 trade marks legally proven to have conceptual similarities with earlier trade marks, which are extracted through a manual analysis of the legal reports obtained from the disputed cases. An excerpt example of a legal report analysed in this process is shown in Figure 5.6. The 55 trade marks pairs are then utilised as the query set to test the retrieval accuracy of the algorithm. The algorithm

Table 5.3 The trade mark pairs extracted from the real court cases

Trademark 1	Trademark 2	Trademark 1	Trademark 2
COOL WATER	AQUACOOL	tripp trapp	TRIP TRAP
Feel'n LEARN	Feel'n SEE	COMPARIS	compare.ch
FRUIT TIGER	LION FRUIT	Freecom	freecom.ch
MAGIC HOUR	MAGIC TIMES	CHANEL	CHANEL
PLANE ocean	AQUA PLANET	AIR FRESH	AERO FRESH
Living Style	Lifestyle	GIANTS	riesen.ch
NAVITIMER	MARITIME	ROYAL ELASTICS	ROYAL ELASTICS
PINK LADY	LADY IN ROSE	Jetbox	JETBOXX
EVOLUTION	revolution	BULL	OX
IT GIRL	It Girl	Car4you	MOTO4YOU
Securitas	SECURICALL	BOTOX	Botoceutical
ON DEMAND	on Demand	VITALITY	Vital
smart home	SmartHome	YELLO	YELLOW
NO NAME	NO NAME	Quiclean	fast clean
THERMAL BALANCE	clima balance	INDEX	1NDICES
FEELGOOD	FEEL GOOD	MAX	MAX
WebFOCUS	FOCUSNET	Feelgood's	FEEL GOOD
MULTI-LINE	multiline	MediData	medidata
RED BULL	BLUEBULL	DEKO LINE	DECOLINE
GREYHOUND	greyhound	BIOPOINT	BIO POINT
EMOTION	emotion	Maxx	max
werkhouse	WERK HOUSE	COMPARIS	comparer.ch
LAWFINDER	LexFind.ch	KICKDOWN	kickdown.ch
STEPSTONE	stepping stone	Bosshard	bosshard.ch
SAVOUR CLUB	CLUB Saveur	SHARK	Hai
Black	WHITE	ORPHAN EUROPE	ORPHAN IINTERNATIONAL
SUGARLAND	SWEETLAND	SECRET PLEASURES	PRIVATE PLEASURES
fair assurance	fair insurance consulting		

The trademarks "FEEL 'N LEARN" and "SEE 'N LEARN" also ultimately suggest very similar meanings. That the verbs "FEEL" and "SEE" by themselves denote different sensory perceptions does not change the fact that both trademarks contain the idea of learning with the aid of sensory organs. This fundamental idea remains in the mind of the consumer, which is why trademark similarity is also affirmed from a semantic point of view (this was also the decision of the RKGE on 21 December 2001, sic! 3/2002172 E. 6 S. 172 – Fly away / Float away).

Figure 5.6 An excerpt from the legal report obtained from one of the infringement cases is tested using six different word similarity measures, which are employed during the similarity comparison computation in step 3 of the algorithm.

is tested using six different word similarity measures, which are employed during the similarity comparison computation in step 3 of the algorithm.

The R-precision score is then computed as a measure for the retrieval accuracy. R-precision is a precision score at the R-th position in the retrieval result, where the precision score is given by the following equation.

$$\text{precision}=\frac{|\text{relevant items}|}{|\text{retrieved items}|} \tag{5.2}$$

In this experiment, since the relevant trade mark for each query is the conflicting trade mark from the cases, it can be assumed that only one relevant trade mark exists in the database. The precision in the first position in the retrieval for each query is thus computed and averaged to obtain the final score.

Result:

Figure 5.7 shows the R-precision score of the proposed retrieval algorithm when employing a different type of word similarity measure in the comparison computation. It also shows the accuracy of the approximate string matching algorithm, which is normally used in a traditional text search. The R-precision score computed in the first experiment measures the capability of the algorithm to retrieve relevant trade marks in the context of conceptual similarity. All results clearly indicate that the algorithm exceeds the performance of approximate string matching by 17.6% to 20.6%. All individual results of the algorithm when using the employed word similarity measures surpass the R-precision score produced by the baseline algorithm.

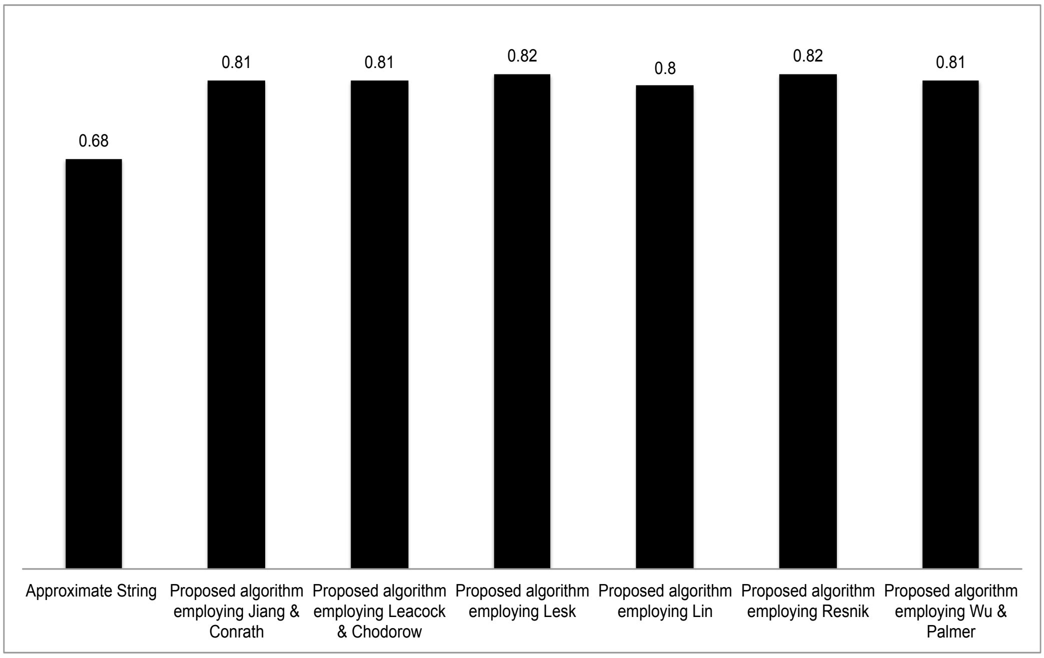


Figure 5.7 R-precision score of the proposed algorithm using different types of word measures and the approximate string matching

As for the performance of the algorithms when employing different word measures, the highest R-precision score is obtained when using the Lesk and Resnik measures. Both produce a score of 0.82, followed by a score of 0.81 from the Wu & Palmer, Jiang & Conrath and Leacock & Chodorow measures. The proposed algorithm produces a 0.80 R-precision score when employing the Lin measure. Thus, it can be concluded that the use of different word similarity measures could affect the performance of the proposed algorithm, although the results are comparable to each other. This aspect is further investigated in the next experiment using an even larger database based on collective human opinion.

5.3.2 Experiment 2 Setup and Evaluation

Experimental Setup:

The objective of this experiment is to evaluate further the performance of the proposed algorithm on a bigger scale, using human collective opinion task. Human collective opinion is used in this evaluation based on the nature of trade mark similarity assessment which involves human perception. Thus it is also important to evaluate the performance of the proposed algorithm from the point of view of human collective judgements despite its good information retrieval performance shown in the previous experiment. The type of task is often referred to as a human intelligence task (HIT) (Snow et al., 2008, Corney et al., 2010). Each HIT is a small portion of a large task, which is distributed among a large group of people, known as workers, who have no contact with each other. The database in this experiment is a database comprised of 378,943 company names in the UK and Australia obtained from (Database).

All the entries in the database are first run as input queries, resulting in a total of six sets of 378,943 retrieval results (corresponding to the six different word measures employed in the proposed algorithm). An analysis of the top retrieved results is performed to find a set of queries that produce at least three result variations from the six sets of results collected. A total of 25 queries are then selected randomly from this set.

Two crowdsourcing tasks were designed to evaluate the performance of the proposed algorithm in comparison with the traditional approximate string matching method. Similar to the previous experiment, the performance of the algorithm when employing different word measures is also examined. Table 5.4 lists the 25 queries used in the crowdsourcing evaluation and the retrieved names of the proposed algorithm implemented when employing the six word similarity measures in the proposed algorithm.

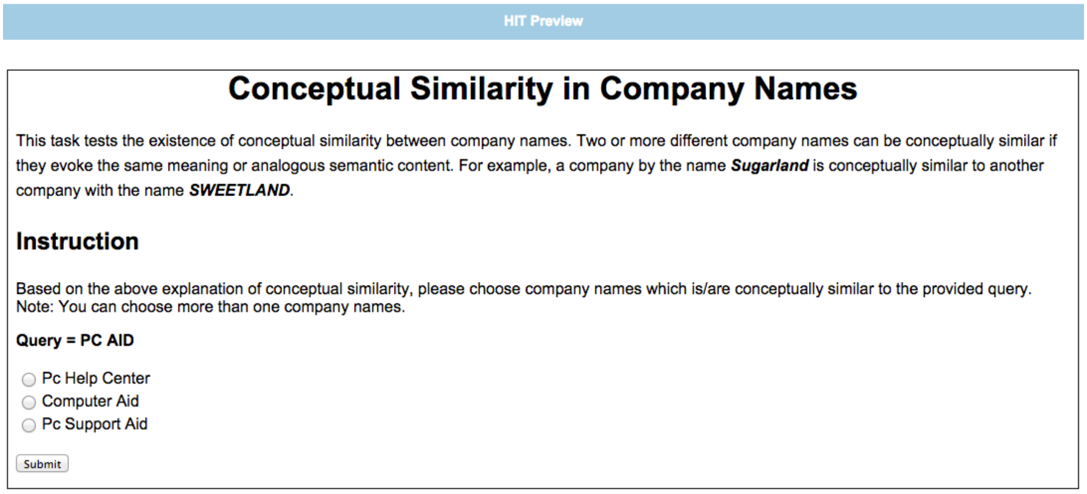
Task 1

This task compares, using human collective opinions, the performance of the proposed algorithm when employing six different measures. In this task, the workers are presented with a query name and three target names. The target names are the company names extracted from the retrieval results with the maximum similarity score from the proposed algorithm, i.e. when the six different word measures mentioned above are employed. In other words, the three target names correspond to three different company names returned by the proposed algorithm when using the six different word measures discussed previously. This also means that two or more results from different word measures may provide similar target names.

For each of the targeted company names, workers are assigned to evaluate whether they are conceptually similar to the query names. The workers are also allowed to choose more than one targeted company name, should they also find them to be conceptually similar. This task consists of 25 HITs. For each HIT, 20 different workers are assigned to complete the task. In total, 500 evaluations are obtained from this task. Figure 5.8 shows one of the HITs created for this task.

Table 5.4 The queries and the highest similarity return names for the six word measures employed in this experiment

Query	Jiang & Conrath	Leacock & Chodorow	Lin	Resnik	Wu & Palmer	Lesk
Red Bull	Red Cover Ltd	The Red Cow	The Red Cow	The Red Lion	The Red Cow	The Red Lion
Imagefast	Instant Image	Smart Image	Snapfast	Smart Image	Smart Image	Instant Image
The Car Doctor	Omega Car Repairs	Specialist Cars	The Car House	The Car House	Specialist Cars	The Car House
Landlook	Landcare	Land Surveys	Landcare	Landcare	Land Surveys	Property Look Ltd
PC AID	Pc Help Centre Ltd	Pc Support Ltd	Pc Support Ltd	Computer Aid	Pc Support Ltd	Pc Support Ltd
Magic Kingdom Ltd	Magic City	Magic Man	Magic City	Dance Kingdom	Magic City	Magic Man
Bodytone	Mind Body Spirit	Build Tone	Build Tone	Body To Burn	Build Tone	Body To Burn
Rug Cleaning Experts	Audley Carpet Cleaning	Master Carpet Cleaning	carpet-cleaning-specialist	Master Carpet Cleaning	Master Carpet Cleaning	carpet-cleaning-specialist
Party Kings	Dancing Queen Parties	The Party Man	Dancing Queen Parties	Ace Party Co.	The Party Man	The Party Man
Global Internet Ltd	Global Network Solutions	Global Web Ltd	Global Radio	Global Web Ltd	Global Web Ltd	Global Web Ltd
The Letter Factory	Mill Letter Signs	The Print Factory	The Type Factory	The Print Factory	The Print Factory	The Print Factory
Bag & Baggage Ltd	Premier Luggage & Bags Ltd	Bag N Box	Suitcases & Bags	Suitcases & Bags	Bag N Box	Bag N Box
Computerman	Human Computer Interaction	The Computer Guy	The Computer Guy	PC Man	The Computer Guy	The Computer Guy
Gas Master	Professional Gas Service	Airmaster	Airmaster	Professional Gas Service	Gas Experts	Airmaster
Pet Pillow	Pets At Rest	The Pet Place	Pet Pad	Pet Pad	The Pet Place	The Pet Place
Oak Tree	The Pine Tree	The Ash Tree	The Pine Tree	Oakwood	The Ash Tree	The Ash Tree
Sushi Kingdom	The Sushi Place	Sushi World	The Sushi Place	Rock Candy Kingdom	Sushi World	Sushi World
Star Ballroom	Planet Ballroom	Star room	Planet Ballroom	Superior Ballroom Pty	Star room	Superior Ballroom Pty
International Displays	Global Displays	Display World Ltd	Expression International	Display World Ltd	Display World Ltd	Expression International
Deep Sea	Deep Ocean Planet	Deep Ocean Planet	Deep Red	Deep Ocean Planet	Seapoint	Deep Red
Planet Magazine	Tatler Magazine	World Magazines ltd	World Magazines ltd	The Daily Planet	World Magazines ltd	World Magazines ltd
First Ideas	An Original Idea	An Original Idea	First Concept Ltd	An Original Idea	An Original Idea	First View
Gold Line	Gold Air International	Goldprint	Goldprint	Silver Line Ltd	Goldprint	Silver Line Ltd
The Knowledge Group	Concept Group Ltd	Power Group Ltd	Concept Group Ltd	Knowledge Pool	Power Group Ltd	Power Group Ltd
The Youth Federation	Youth Association	Youth Association	Youth Club	Youth Service	Youth Association	Youth Association


HIT Preview

Conceptual Similarity in Company Names

This task tests the existence of conceptual similarity between company names. Two or more different company names can be conceptually similar if they evoke the same meaning or analogous semantic content. For example, a company by the name ***Sugarland*** is conceptually similar to another company with the name ***SWEETLAND***.

Instruction

Based on the above explanation of conceptual similarity, please choose company names which is/are conceptually similar to the provided query.
Note: You can choose more than one company names.

Query = PC AID

- Pc Help Center
- Computer Aid
- Pc Support Aid

Submit

Figure 5.8 HIT example for task 1 in the experiment

Task 2

The main objective of Task 2 is to compare the relative performance of the proposed algorithm against the baseline algorithm, i.e. the approximate string matching algorithm, using a collective human judgment in the modus operandi. The result of the proposed algorithm, when employing the Wu & Palmer's word measure, is utilised in this experiment due to the findings in the previous task. In this task, three company names that represent the top three highest similarity results retrieved using the proposed algorithm are compared against the top three retrieval results when using the approximate string matching technique. In the HIT designed for this task, workers are asked to complete a pairwise comparison in which they rate the similarity between a pair of company names (i.e. the query name and the targeted company name, which is one of the top three retrieval results).

Figure 5.9 shows an example of the HITs assigned in this task in which the workers are asked to rate the similarity of the pair names from highly similar to

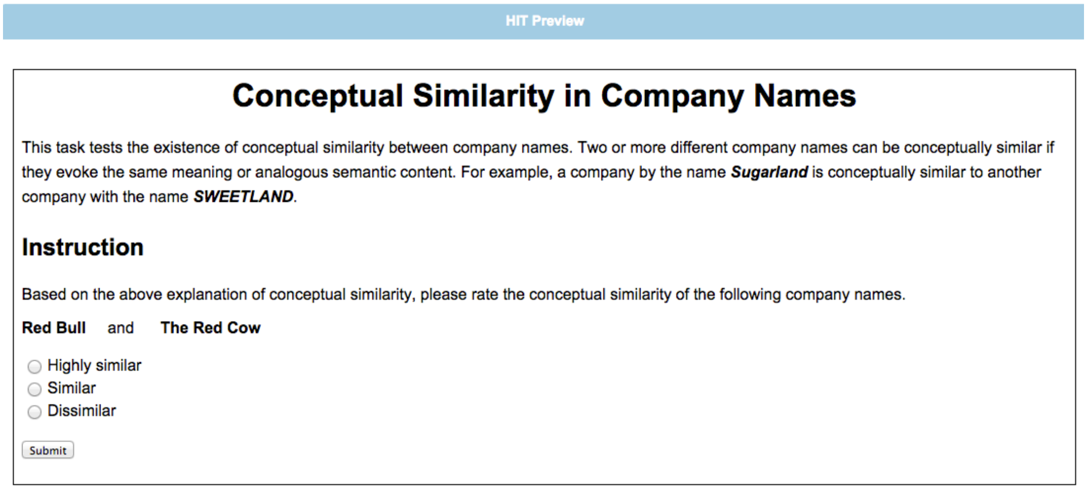


Figure 5.9 Hit example of task 2 in the experiment

dissimilar. Twenty different workers are assigned for each query; corresponding to a total of 25 x 3 x 20 HITs produced from the results generated using the proposed algorithm. Similar HITs are also prepared in the same manner for the retrieval results obtained when using the approximate string matching technique, totalling 3,000 HITs altogether.

Result:

__Task 1__

A score of 1 is assigned to the targeted company names, which has been judged to be conceptually similar by the evaluators from each HIT. Next, the average score in the range of 0 to 1 (0 being the worst score and 1 being the best score) from 20 different workers (i.e. 20 HITs) is computed for each query, as shown in Table 5.5. The results are further analysed by sorting the average score into five scoring bands (i.e. the 0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8 and 0.8-1). Table 5.6 displays the results for the scoring bands, obtained using the six word similarity measures.

The results from the first task of the second experiment show a similar pattern to those produced in the first experiment, in which there is a variation of scores across the table, as shown in Table 5.5. The results from the table also suggest that the proposed algorithm produces the highest score when using the Wu & Palmer word measure with an average score of 0.66 (as shown at the bottom of the table). This is followed by the average scores produced using the Leacock & Chodorow and Lin measures, both scoring 0.63, the Lesk measure, 0.53 and the Resnik and Jiang & Conrath measures, 0.52. Likewise, the band scoring result analysis from Table 5.6 shows that results obtained when employing the Wu & Palmer and the Leacock & Chodorow measures, produce the highest score for the band above 0.6, in which both have a cumulative count of 18. However, the Wu & Palmer measure produces a slightly better score in the band above 0.8, with a count of 10. Although Lin's measure produces the highest score in the band above 0.8, with a count of 11, its total count for the band above 0.6 is 14, 16% less than the count produced by both the Wu & Palmer and the Leacock & Chodorow measures. Furthermore, the Wu & Palmer measure also produces a better R-precision score in the previous experiment compared to the Lin measure. In general, the scores between the three measures in this part of the experiment are comparable to each other. However, since 72% of the results when using the Wu & Palmer measure produce scores above 0.6, together with the low-complexity nature of its computation and the results from the previous experiment, this measure is considered a viable choice to be incorporated into the proposed algorithm.

Table 5.5 The average score of each query using the word measure employed in this experiment

Queries	Jiang & Conrath	Leacock & Chodorow	Lin	Resnik	Wu & Palmer	Lesk
Red Bull	0	0.9	0.9	0.45	0.9	0.45
Imagefast	1	0	0.7	0	0	1
The Car Doctor	0.7	0.7	0.25	0.25	0.7	0.25
Landlook	0.4	0.7	0.4	0.4	0.7	1
PC AID	0.7	0.6	0.6	1	0.6	0.6
Magic Kingdom Ltd	1	0	1	0	1	0
Bodytone	0	0.95	0.95	0.1	0.95	0.1
Rug Cleaning Experts	0.7	0.75	0.5	0.75	0.75	0.5
Party Kings	0.5	0.7	0.5	0.1	0.7	0.7
Global Internet Ltd	0.35	1	0.15	1	1	1
The Letter Factory	0	0.8	0.85	0.8	0.8	0.8
Bag & Baggage Ltd	0.8	0.4	0.9	0.9	0.4	0.4
Computerman	0	1	1	1	1	1
Gas Master	0.45	0.6	0.6	0.45	1	0.6
Pet Pillow	0.25	0	1	1	0	0
Oak Tree	0.55	0.55	0.55	0.6	0.55	0.55
Sushi Kingdom	0.45	1	0.45	0	1	1
Star Ballroom	0.8	0.75	0.8	0.15	0.75	0.15
International Displays	1	0.6	0.1	0.6	0.6	0.1
Deep Sea	0.9	0.9	0.05	0.9	0.15	0.05
Planet Magazine	0.05	0.9	0.9	0.35	0.9	0.9
First Ideas	0.65	0.65	0.95	0.65	0.65	0.2
Gold Line	0.1	0.2	0.2	0.7	0.2	0.7
The Knowledge Grou	0.55	0.2	0.55	0.8	0.2	0.2
The Youth Federation	1	1	0.9	0	1	1
Average Score	0.52	0.63	0.63	0.52	0.66	0.53

Table 5.6 The average scores across the bands for each word measure employed in this study

Scoring Band	Jiang & Conrath		Leacock & Chodorow		Lin		Resnik		Wu & Palmer		Lesk	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
0<=x<0.2	6	24%	3	12%	3	12%	7	28%	3	12%	6	24%
0.2<=x<0.4	2	8%	2	8%	2	8%	2	8%	2	8%	3	12%
0.4<=x<0.6	6	24%	2	8%	6	24%	3	12%	2	8%	4	16%
0.6<=x<0.8	4	16%	9	36%	3	12%	5	20%	8	32%	4	16%
0.8<=x<=1	7	28%	9	36%	11	44%	8	32%	10	40%	8	32%

Task 2

Table 5.7 displays the retrieval results produced by the proposed retrieval algorithm and the approximate string matching algorithm. A scoring analysis similar to the one used in Task 1 is then performed, which has resulted in the scoring shown in Table 5.8. The average score from 20 different workers for each unique HIT is computed in the range of 0 to 2 (0 being the worst score and 2 corresponding to the best score). These scores are further analysed and grouped into four scoring bands (i.e. 0–0.5, 0.5–01.0, 1.0–1.5 and 1.5–2.0, as shown in Table 5.9).

The analysis of the results of the second task in this experiment seeks to compare the performance of the proposed algorithm with approximate string matching as the baseline algorithm. The scores produced by the proposed algorithm exceed those generated when using the traditional approximate string matching algorithm on all 25 queries (Table 5.8). The average score of the proposed algorithm (i.e. the scores at the bottom of Table 5.8) for Result 1, Result 2 and Result 3 (i.e. the first three results) exceeds the approximate string matching average score by 99%, 153% and 116%, respectively. Similarly, the results according to the band score analysis shown in Table 5.9 further justify the applicability of the proposed algorithm, as it produces much better scores than the baseline algorithm. This indirectly proves that a traditional search is not suitable for a trade mark search based on conceptual similarity. Such type of retrieval can be performed using the proposed algorithm, which employs a lexical knowledge source to grasp the conceptual content of trade marks.

Table 5.7 The three retrieval results from the proposed algorithm and the approximate string matching algorithm

Query	Proposed Retrieval Algorithm			Approximate String Matching Algorithm		
	Result 1	Result 2	Result 3	Result 1	Result 2	Result 3
Red Bull	The Red Cow	The Red Lion	Red The Cat	ed Bull	Red Cell	J.R Bull
Imagefast	Smart Image	Instant Image	Snapfast	Imageset	Imageware	Images
The Car Doctor	Specialist Cars	The Car House	Car Medic	The Cue Doctor	The Chair Doctor	The Tap Doctor
Landlook	Land Surveys	Landcare	Property Look Pty	Landmark	Ladbrook	Panelock
PC AID	Pc Support Ltd	Working PC	Computer Aid	P C A D	P H D	P C I
Magic Kingdom Ltd	Magic City	Magic Man	Magic World	Manor Kingdom Ltd	Gaggia Kingdom Ltd	Magic Junior Ltd
Bodytone	Build Tone	Shape and Tone	Bodytalk	Body Zone	Bodyline	Bodycote
Rug Cleaning Experts	Master Carpet Cleaning	Superstar Carpet Cleaning	carpet-cleaning-specialist	can Clothing Exports	Rendering Experts	Rgs Cleaning Ltd
Party Kings	The Party Man	Party Land	Ace Party Co.	Party Kegs	Party Link	Party Pieces
Global Internet Ltd	Global Web Ltd	Global Link	Global Radio Ltd	Power Internet Ltd	Sos Internet Ltd	Global Journey Ltd
The Letter Factory	The Print Factory	The Language Factory	The Type Factory	The Monster Factory	The Flower Factory	The Guitar Factory
Bag & Baggage Ltd	Bag N Box	Baggage Express	Suitcases & Bags	Bag & Bale Ltd	B T S Haulage Ltd	Maxi Haulage Ltd
Computerman	The Computer Guy	PC Man	Computer People	Computerden	Computermark	Computerland
Gas Master	Gas Experts	Airmaster	Professional Gas Service	Gas Matters	Car Master	G P Masters
Pet Pillow	The Pet Place	Pet Pad	Pets At Rest	Pete Hill	Pete Millson	Pet Pals
Oak Tree	The Ash Tree	The Olive Tree	The Walnut Tree	Oakmere	Fab Tec	Oakdene
Sushi Kingdom	Sushi World	The Sushi Place	Kingdoms Seafood	Cats Kingdom	Dance Kingdom	Pets Kingdom
Star Ballroom	Star room	Superior Ballroom Pty Ltd	Planet Ballroom	Star room	Sea Bloom	Smart Bathrooms
International Displays	Display World Ltd	Screen International	Expression International	International Diamalt	International Billiards	International Fitness
Deep Sea	Seapoint	Sea Start Ltd	Deep Ocean Planet	Deep Red	Dee Cee	Deep C
Planet Magazine	World Magazines ltd	The Daily Planet	Magazine Creation	Piano Magazine	Flyer Magazine	Sleaze Magazine
First Ideas	An Original Idea	First View	First Impressions	First Steps	Right Ideas	Light Ideas
Gold Line	Goldprint	Silver Line Ltd	Lacegold	Fjord Line	Goldprint	Goldwins
The Knowledge Group	Power Group Ltd	Process Group	Knowledge Pool	The Knowledge Base	The Holiday Group	The Lowe Group
The Youth Federation	Youth Association	Youth Club	Youth Service	The Youth Media Ltd	The Louth Leader	Nhs Support Federation

Table 5.8 The average scores between the proposed algorithm and the approximate string matching algorithm

Queries	Result 1		Result 2		Result 3	
	Proposed Algorithm	Approximate String	Proposed Algorithm	Approximate String	Proposed Algorithm	Approximate String
Red Bull	1.55	0.7	0.8	0.4	0.5	0.2
Imagefast	0.65	0.6	1.7	0.95	1.05	0.95
The Car Doctor	1	0.3	0.55	0.35	0.9	0.35
Landlook	1.05	0.9	0.65	0.2	0.9	0.1
PC AID	1.55	0.55	0.7	0	1.8	0.2
Magic Kingdom Ltd	1.4	0.85	0.5	0.5	1.45	0.55
Bodytone	1	0.9	1.1	1	0.9	0.9
Rug Cleaning Experts	1.45	0	1.65	0.2	1.6	1.2
Party Kings	1.1	0.65	0.75	0.75	0.65	0.6
Global Internet Ltd	1.8	1	0.85	0.75	0.5	0.5
The Letter Factory	1.15	0.2	0.6	0.3	1	0.2
Bag & Baggage Ltd	0.8	0.75	1.1	0.4	1.55	0.35
Computerman	1.65	0.95	1.9	0.9	1.55	1.2
Gas Master	1.65	1.05	0.6	0.6	1.1	0.45
Pet Pillow	0.55	0	1.5	0	0.5	0.5
Oak Tree	1.05	0.7	0.75	0	0.9	0.35
Sushi Kingdom	1.6	0.2	1.35	0.15	0.6	0
Star Ballroom	1.35	1.3	1.1	0	1.1	0.1
International Displays	1.55	0.4	0.8	0.35	0.6	0.2
Deep Sea	0.5	0.25	0.5	0.4	1.25	1
Planet Magazine	1.1	0	1.1	0.35	0.45	0.2
First Ideas	1.25	1.15	1.2	0.35	1.3	0.5
Gold Line	0.6	0.15	1	0.85	0.85	0.25
The Knowledge Group	0.75	0.7	1.45	0	0.55	0.15
The Youth Federation	1.65	0.7	1.55	0.4	0.75	0.25
Average Score	1.19	0.598	1.03	0.406	0.972	0.45

Table 5.9 The average scores across the bands between the proposed algorithm and the approximate string matching algorithm

Scoring Band	Result 1				Result 2				Result 3			
	Proposed Algorithm		Approx. String		Proposed Algorithm		Approx. String		Proposed Algorithm		Approx. String	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%
0<=x<0.5	0	0%	9	36%	0	0%	17	68%	1	4%	15	60%
0.5<=x<1	6	24%	12	48%	12	48%	7	28%	13	52%	7	28%
1<=x<1.5	11	44%	4	16%	8	32%	1	4%	7	28%	3	12%
1.5<=x<=2	8	32%	0	0%	5	20%	0	0%	4	16%	0	0%

Although the proposed algorithm generally produces relevant results during the retrieval process, there are a few cases in which the algorithm returns conceptually irrelevant names, such as the results for the query ‘DeepSea’, which returns ‘Seapoint’, ‘Sea Start Ltd’ and ‘Deep Ocean Planet’. ‘Deep Ocean Planet’ is likely to be more similar to ‘DeepSea’ than ‘Seapoint’ and ‘Sea Start Ltd’. Both ‘Seapoint’ and ‘Sea Start Ltd’ share the same token (i.e. ‘sea’), and both have an equal number of tokens (i.e. two tokens). In general, the tokens ‘deep’ and ‘point’ or ‘deep’ and ‘start’ do not seem to evoke a similar meaning in this context. However, in the lexical hierarchy, one of the senses belonging to ‘deep’, described as ‘the central and most intense or profound part’, is a hyponym of ‘middle’, defined as the ‘time between the beginning and the end of a temporal period’. Apparently, this specific sense of the word ‘middle’ is also a hyponym of the word ‘point’, described as ‘an instant of time’. For this particular sense belonging to both ‘deep’ and ‘point’, the path length is only two nodes away. In the same manner, the path length between ‘deep’ and ‘start’, described as ‘the time at which something is supposed to begin’, is three nodes away. For this specific part of the WordNet tree, the ‘point’ node is the common subsumer that subsumes ‘start’ and ‘deep’.

In general, the shortcomings pointed out in the previous paragraph suggest that, although the conceptual similarity comparison of trade marks is made possible using the proposed algorithm, it is still highly dependent on the lexical ontology employed. Another point to note is that a trade mark is considered a very short sentence in which choosing the most appropriate sense for the trade mark in question is highly challenging due to the limited number of words comprising the trade mark. This limitation makes the common word sense disambiguation technique that considers neighbouring words inapplicable in this context.

The results from the experiment performed in this study also confirm that the conceptual similarity comparison of trade marks can be addressed using linguistic sources, such as a lexical ontology and lexicons. The algorithm developed in this study provides a generic mechanism for such a comparison. For example, the algorithm is not limited to the use of a specific word measure. This advantage provides certain flexibility in choosing a word measure or lexical resource deemed to suit specific applications or requirements.

5.4 Summary

This chapter fulfils the third objective of this study by proposing a semantic algorithm to compare the conceptual similarity between trade marks. The algorithm brings forward an entirely new similarity comparison concept in the domain of trade mark retrieval. It utilises natural language processing, together with an external knowledge source in the form of a lexical ontology. The evaluation using both information retrieval measures and human judgment shows a significant improvement, as the algorithm provides better results than the traditional baseline technique. In addition, the algorithm is not limited to the use of a specific word measure. This advantage provides flexibility to choose any word measure suitable for particular applications or requirements. The results from the experiment performed in this study confirm that the comparison of trade marks based on their conceptual similarities can be conducted using linguistic sources.

Chapter 6

Trade Mark Assessment based on Phonetic Similarity

Phonetic similarity comparison between trade marks is one of the fundamental similarity aspect examined during infringed trade mark cases and is of highly important criteria that is analysed during trade marks registration. In a nutshell, phonetic similarity examination deals with the sound/aural aspect of the trade marks text i.e. the pronunciation of the trade marks when the average consumers utters the trade marks.

Thus, this chapter addresses the fourth objective of this thesis by proposing a trade mark retrieval algorithm that compares and retrieves trade marks based on their phonetic similarity. The chapter is organised as follows. Section 6.1 describes the requirement needed for the phonetic comparison and Section 6.2 introduces the proposed algorithm. The experimental evaluation of the proposed algorithm together with the results are then presented in Section 6.3 and Section 6.4 summarises this chapter.

6.1 Phonetic Similarity Comparison Requirement

The following list discusses the four fundamental criteria that need to be included during the trade mark examination using phonetic similarity aspect, based on the guideline provided in the trade mark manual (OHIM, 2012c), together with the finding in cognitive research and forensic linguistic practice. The criteria presented in this chapter forms a basic understanding that distinguish the phonetic similarity developed in this chapter from the phonetic similarity used in other application such as those in genealogy and computational linguistic. As such the proposed similarity comparison algorithm presented in this chapter is designed to accommodate these three criteria. The criteria are as follows:

1. According to the trade mark manual, the common rhythm and intonation of trade marks plays an important role in how signs are perceived phonetically. As defined in (Collins, 2014), *"rhythm"* is the arrangement of words into a more or less regular sequence of stressed and unstressed, and *"intonation"* is the sound pattern of phrases and sentences produced by pitch variation in the voice. The definition clearly shows the phonology requirement in determining the phonetic similarity between trade marks. Thus, the trade mark phonetic similarity algorithm should allow phonetic search by means of phonological similarity computations that can fulfil the similarity examination requirement outlined in the trade mark manual. This requirement also fits the claim made by forensic linguistic studies that require a phonological feature transformation and analysis when dealing with the phonetic similarities of trade marks (Butters, 2007). A direct conversion, such as the one employed in *Soundex*, a commonly used phonetic algorithm in name matching application normally used in genealogy,

Table 6.1 Example of trade mark dispute cases which involve typography symbols (OHIM, 2012c)

Earlier sign	Contested sign	Case No
D&G	DNG	R 0160/2010-2 The ampersand '&' will be pronounced in most European Union languages and is recognised as the corresponding translation of the conjunction 'and'.

although based on the phonological pattern of graphemes, does not represent enough phonological properties. Thus, a string phonetic similarity algorithm derived based on phonological features e.g. human speech articulation, is more applicable in this study.

2. The algorithm should also be able to address the phonetic similarities of trade marks consisting of typography symbols in which, according to the trade mark manual, they do have phonetic features and therefore, thus they must be considered accordingly. Table 6.1 shows examples of trade mark cases with phonetic similarity, provided in the OHIM trade mark manual.

3. The algorithm should also take into account the overall phonetic similarities between the trade marks that may exist as a phrase. This is highly relevant for trade marks with more than one word. The manual (OHIM, 2012c) clearly states that if there exists words that are identical or similar but in a different order and re-arrangement of those words would result in phonetically identical or highly similar features, those trade marks would therefore be concluded to have phonetic similarities. Hence, the re-arrangement of the words that constitute a

trade mark should also be addressed properly. Table 6.2 shows several examples of such cases.

4. The algorithm should consider the relative importance of the beginning and ending part of the trade marks as compared to the rest of the part in the trade mark text. This is due to the finding in cognitive research together with the common practice of forensic linguist when analysing trade mark similarity in infringement disputed cases. The trade mark manual also provides clear trade mark dispute examples pertaining this criterion, which can be seen in Table 6.3

Table 6.2 Example of trade mark dispute cases that have similar words but in different order (OHIM, 2012c)

Earlier sign	Contested sign	Case No
SAT-COM	COM S.A.T	B 361 461
Kids Vits	VITS4KIDS	T-484/08 (C-84/10 P dismissed)
HEDGE INVEST	InvestHedge	T-67/08

Table 6.3 Examples of trade marks cases: (a) the dissimilar cases, (b) the cases that has phonetic similarity (OHIM, 2012c)

Earlier sign	Contested sign	Relevant territory	Case No
ARCOL	CAPOL	EU	C-193/09
CLENOSAN	ALEOSAN	ES	R 1669/2010-2
GULAS	MARGULIÑAS	ES	R 1462/2010-2

(a)

Earlier sign	Contested sign	Relevant territory	Case No
FEMARA	Femagro	EU	R 0722/2008-4
4US	For US	BX	R 0166/2010-1
HCOIL	HELI-COIL	DE	R 1071/2009-1 similar to a low degree

(b)

6.2 The Proposed Comparison and Retrieval Algorithm based on Phonetic Similarity

The proposed trade mark comparison and retrieval algorithm advances the study in this area by providing a mechanism to compare trade marks based on their phonetic similarity. The algorithm is developed based on the trade mark phonetic comparison requirement as outlined in the trade mark manual together with previous study in cognitive science. In addition to that, the algorithm also enables the similarity computation of trade marks with typographic characters. Phonological features are used in the algorithm to provide better scientific justification in the similarity computation.

A flowchart representing the proposed retrieval algorithm is shown in Figure 6.1. The proposed algorithm consist of two modules namely the offline module and the online retrieval module. In both modules, each trade marks from the database are pre-processed using several natural language processing (NLP) processes such as string tokenization. They are then screened to detect the existence of typography symbols, followed by four main steps. The following discusses four main steps involved in the algorithm:

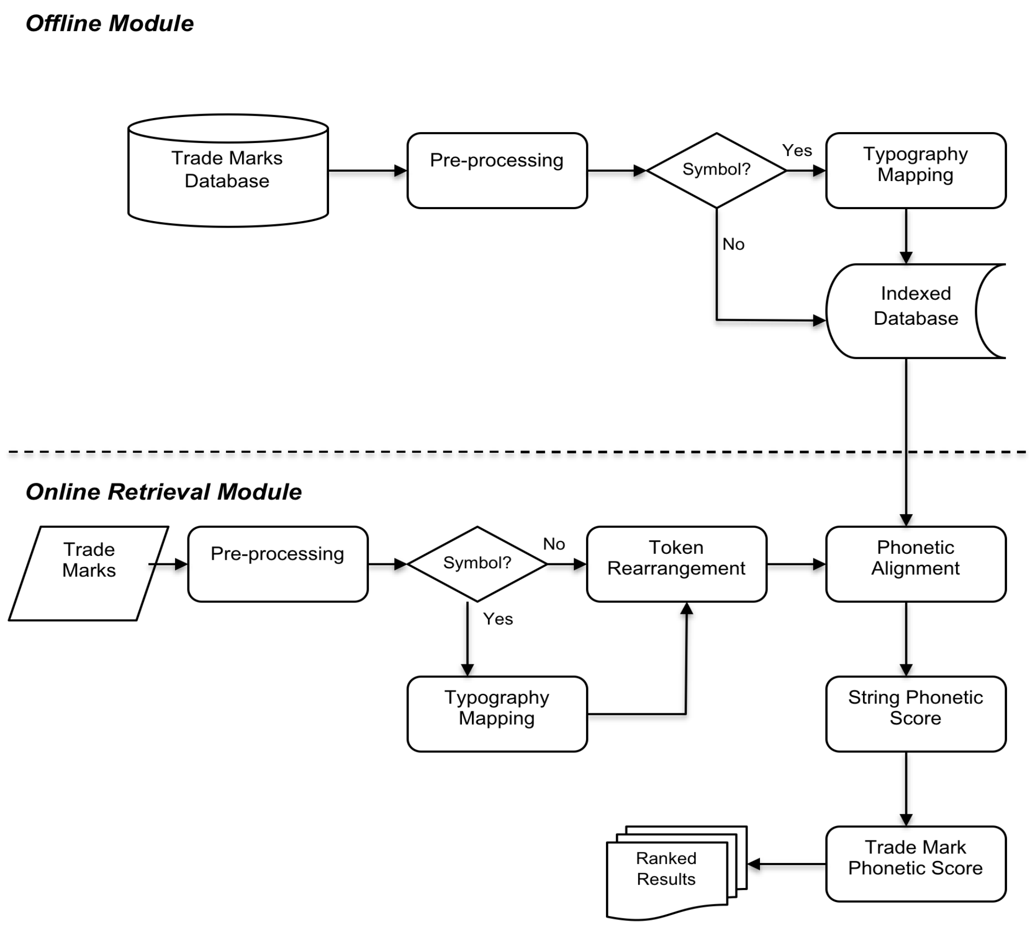


Figure 6.1 A flowchart representing the proposed retrieval algorithm

1. Typography Mapping

Upon the symbol detection, the trade marks with typography symbols are then converted into standard graphemes i.e. letters, and concatenated. The conversion allows the phonetic computation score of the typography symbols in a more standard and natural manner, similar to the regular words. It is performed through a mapping exercise to determine the relationship between the detected symbols or special characters to their meaning. A library of symbols or special characters with their corresponding meanings is manually established based on a list of number and symbols, as a proof of concept. The steps taken at this particular stage of the algorithm are to address the second criteria, as outlined in the beginning of this chapter. The typography mapping is the only main process also performed in the offline module besides the pre-processing. The trade marks are then indexed and stored in a separate database for use during similarity computation in the online module.

2. Token Re-arrangement

In the token rearrangement step, the token sets extracted from the trade mark words are rearranged through a permutation operation. For example, as shown in Table 6.2, a trade mark "HEDGE INVEST consisting of two tokens, produces two sets of token arrangements, i.e., (*hedge, invest)* and *(invest, hedge).* The permutation of the token set provides a means of token rearrangement, which is needed when determining the overall phonetic similarity computation of the trade marks against others. This step, therefore, serves the third criteria mentioned in the first section of this chapter. Each permutated token set is then concatenated into a

```
Pseudocode: /*comment*/
/* This part of the code is performed for the typography
       mapping and the token alignment steps developed in the algorithm*/
define Tq as the input trade mark query;
for every letter in Tq
       { check for any symbols or numbers;
        if Tq contains symbols or numbers;
               {map the corresponding symbols with its meaning;
                 replace the symbols in Tq with mapped meaning;}
   Tqmap=Tq;}
      token_q=tokenize(Tqmap)
       if the number of token in token_q>1
       {perm_q=permutes the token set in token_q;
         con_q=concatenate each token set in perm_q;}
      else
    {con_q=token_q;}
```

Figure 6.2 A pseudo code of the typography mapping and token alignment steps developed in this retrieval algorithm

string to find the best match for string phonetic similarity computation in the next step. Figure 6.2 shows a pseudo code describing the typography mapping and the token alignment steps developed during the initial two steps of this retrieval algorithm.

3. Optimal String Alignment Computation

An optimal string alignment is an alignment between two strings that maximizes the overall phonetic similarity score between the trade mark string. Thus, the string alignment and string phonetic score computation between the permutated token set of the query trade marks and the trade marks stored in the database are then performed simultaneously using dynamic programming approach to achieve the targeted optimal string alignment. The algorithms are employed from the work developed in (Kondrak, 2003), which is known as the ALINE algorithm. ALINE offers global and local alignment in the computation of phonetic similarity. In this study, global alignment is employed due to trade mark phonetic comparison concept that focuses on the overall level of similarity (Kessler, 2005).

The employed string phonetic similarity computation, computed on the optimised alignment between two strings, is developed based on phonological features derived from human speech production. It assigns large positive score to phoneme pairs, which are similar, large negative score to dissimilar pairs and small negative score to insertion or deletion operations (Kondrak, 2003). The algorithm is employed due to its computational approach which is based on the phonological features and therefore provides a stronger scientific basis for the metrics used in the algorithm and eliminates some of the innate weaknesses of the approach used in many other phonetic algorithm e.g. *Soundex* and *Phonix* algorithms, which are used in name matching algorithm in genealogy study. Therefore, the employed string phonetic algorithm fulfils the first criteria outlined at the beginning of this section by employing a phonological-based string similarity algorithm in the trade mark phonetic similarity computation.

In addition, the algorithm has also been employed in the study of similarity comparisons in drug names (Kondrak and Dorr, 2006) and has been incorporated as the basis of a system developed for the U.S. Food and Drug Administration for the detection of confusing drug names. Table 6.4 lists the phonological features together with its numerical feature values, employed within the algorithm. The algorithm then assigns a similarity score to each pair of phonemes-based on a weighted multi-feature analysis of both consonants and vowels.

Table 6.4 List of phonological features and the numerical feature values employed in the computation of string phonetic similarity (Kondrak, 2003)

Phonological Features	Numerical Values
Place	bilabial : 1.0 labiodental : 0.95 dental : 0.9 alveolar : 0.85 retroflex : 0.8 palato-alveolar : 0.75 palatal : 0.7 velar : 0.6 uvular : 0.5 pharyngeal : 0.3 glottal : 0.1
Manner	stop : 1.0 affricate : 0.9 fricative : 0.8 approximant : 0.6 high vowel : 0.4 mid vowel : 0.2 low vowel : 0.0
High	high : 1.0 mid : 0.5 low : 0.0
Back	front : 1.0 central : 0.5 back : 0.0
Syllable	1.0
Voice	1.0
Nasal	1.0
Retroflex	1.0
Long	1.0
Round	1.0
Lateral	1.0
Aspirated	1.0

4. Trade mark Phonetic Similarity Score Computation

The phonetic scores for trade mark similarity computation are an arithmetically weighted means of both the phonetic scores from the employed string phonetic algorithm and an individual phonetic score of the first and last phonemes of the trade marks in comparison. The additional scores are incorporated based on cognitive research (Hahn and Bailey, 2005) that demonstrates the relative importance of the beginning and ending phonemes of a word to its overall phonetic similarity comparison. This is also supported by the normal practices of forensic linguists when analysing trade mark similarities for infringement cases (Butters, 2008).

Hence, the trade mark phonetic similarity score between two trade mark strings, T_a and T_b, is as follow:

$$\begin{aligned} \mathrm{sim}(T_a, T_b) = {} & \frac{2 * \mathrm{PhoS}(T_a, T_b)}{\mathrm{PhoS}(T_b) + \mathrm{PhoS}(T_b)}\alpha + \\ & \left(\frac{2 * \mathrm{PhoS}(T_a(0), T_b(0))}{\mathrm{PhoS}(T_b(0)) + \mathrm{PhoS}(T_b(0))} + \right. \\ & \left. \frac{2 * \mathrm{PhoS}(T_a(\mathrm{end}), T_b(\mathrm{end}))}{\mathrm{PhoS}(T_a(\mathrm{end})) + \mathrm{PhoS}(T_b(\mathrm{end}))}\right)(1-\alpha) \end{aligned} \tag{6.1}$$

where $PhoS(T_a,T_b)$ is the maximum phonetic score between string T_a and T_b, produced when T_a and T_b are optimally aligned, and calculated according to (Kondrak, 2003); α is the weighting parameter for the parametric equation; $PhoS(T_a(0),T_b(0))$ and $PhoS(T_a(end),T_b(end))$ are the individual phonetic similarity scores of the first and last letter of the trade marks in comparison. The algorithm is tested on different sets of α values in the range of [0,1] and the optimum performance obtained for the tested database is 0.8.

6.3 Experimental Setup and Evaluation

This section discusses the experimental setup established for the performance evaluation of the proposed algorithm. It comprises two subsections. The first sub-section describes the database employed in this study, followed by a subsection that explains the evaluation method used in this experiment.

6.3.1 Database

The database used in this study comprises 1,400 trade marks obtained from trade mark dispute cases from the years 1999-2012 (Database-Court-Cases), the identical database used in the development of conceptual similarity algorithm described in the previous chapter. The database consists of trade mark words with three types of similarity levels, i.e., visual, phonetic and conceptual. For each of the trade mark dispute cases, a collection of summarised court reports are obtained and manually categorised and analysed for evaluation.

Similar to other information retrieval based evaluation, a query set database is constructed for the testing purpose. Thus, a total of 120 trade marks from 60 dispute cases are then extracted from the database as the query set. The list of the 120 trade marks used in this experiment is shown in Table 6.5. The 120 trade marks are selected based on court case summary reports that find the existence of phonetic similarities between the contesting trade marks. Figure 6.3 provides an excerpt of a trade mark court case report, which shows the comment made by the trade mark expert presented to the court, which concludes the existence of phonetic similarity between the contested trade marks.

Table 6.5 List of the trade marks used in the experiment

Trade Mark 1	Trade Mark 2	Trade Mark 1	Trade Mark 2
FEMARA	Femagro	FMH	FNH
4 US	FOR US	AMORA	AMORE
SAT COM	COM S.A.T	Hedge Invest	InvestHeadge
AURA	AUREA	FENDI	Flenddy
KIK	Quick	AURUS	AURO
Minipic	Minipicks	Viagra	Viaguara
SIN	SKIN	IMAC	IMAX
Zero	Zerorth	SALIXYL	CILIXYL
Audatex	INDATEX	ELSIE	elsa
SANZEZA	SANTHERA	AESCULAP	AESKULAP
Anginol	Angiol	HARRY POTTER	HARRY POPPER
Caliterra	CASA TERRA	Rollstat	ROLL-O-STAT
Rivotril	RIMOSTRIL	Prevista	PREVISA
MOBILAT	MOBIGEL	Preton	PREBETON
CYREL	CYRA	D&G	DNG
ISOTAN	ISOTEC	Euro2008	€08
LINLIF	GIMLIF	Far	FARE
SWISS TALER	Svizze-rotaler	M24	N24
COMBINO	Confino	Zirh	SIR
KIMBO	BIMBO	Cicar	Zipcar
Frangelico	FRAGOCELLO	FERCREDIT	f@irCredit
TWIX	TRIX	ishine	Iceshine
RETROVIR	REBOVIR	Seycos	SEIKO
Stoxx	Stokx	ENTELECT	INTELECT
CH888	8888	F 1	F One
WARIS	WAYSIS	TEA A MO	TIAMO
N-GAGE	CENGAGE	Cristal	Crystal
Chantre	Shantre	Accert	Accet
JOOLA	JOYA	VITS4KIDS	KIDS VITS
ARAVA	Axara	Seventy	Seventees

In the present case, the word marks "SWISS TALER" face (the opposing trade mark) and "Svizze-rotaler '(contested mark). The different spelling of the two characters (upper case as opposed to lowercase) does not fall moderately significant (sic RKGE in 2001, 813 - VIVA / Coop Viva). The contested mark has acquired the brand element 'TALER "of the earlier mark. Moreover, there are **phonetic** and visual levels of similarities between the signs that constituents "SWISS" and "Svizzero". Since there are visual similarities between the letters "W" and "V" and "S" and "Z" and similar pronunciations of "SWISS" and "Svizz-," the only difference is the additional character element, "ero-" in the contested trademark. The matching feature outweighs the deviation in the middle of the words. This is especially true of middle syllables, which usually have only a slight impact on the overall impression of the mark.

Figure 6.3 An example of the court case report

6.3.2 Method of Evaluation

The performance of the proposed algorithm is evaluated using the information retrieval assessment score, i.e., the R-precision score. R-precision computes the precision of a retrieval system at the R-th rank. The rationale of using this measure is due to the nature of the database employed in this study i.e. the trade mark dispute cases which consist of 700 trade mark pairs. Thus, for each query used in the experiment, it has only one relevant item, the precision is therefore computed at the first position in the ranking results. The proposed algorithm is then tested against the original ALINE algorithm and another commonly used orthographic based similarity algorithm, i.e., the edit distance measure (Konstantinidis, 2007), as the baseline. The comparison against the edit distance algorithm is to observe the performance of the proposed algorithm against one that is used in the existing trade mark systems. The edit distance algorithm, also known as the Levenshtein distance, computes similarities by counting the minimum number of operations required to transform one string into the other through substitution, deletion, and insertion operations.

For evaluation purposes, the R-precision score of the proposed algorithm, the original ALINE algorithm, and the edit distance algorithm, is computed on each query (the 120 trade marks from the database). The average of all the scores given by the 120 queries is then computed to represent the performance score of the corresponding algorithms.

6.3.3 Result

Table 6.6 displays the R-precision score obtained from the proposed algorithm in comparison with the ALINE and the edit distance algorithms. The proposed algorithm produces a 0.81 R-precision score, exceeding the performance of the original ALINE phonetic scores by 14%.

In comparison with the baseline algorithm, a commonly used orthographic algorithm for string similarity matching, i.e., edit distance, the proposed algorithm score improves the R-precision score by 17%. The improvements achieved by this result are as anticipated, since the trade mark database employed in this study comprises a number of typography trade marks and trade mark pairs with different word arrangements, conditions that are neither addressed nor considered in both ALINE and edit distance algorithms.

Table 6.6 The R-precision scores of the proposed algorithm, the ALINE algorithm, and the edit distance algorithm

Algorithms	Edit Distance Algorithm	ALINE Algorithm	Proposed Algorithm
R-Precision Score	0.69	0.71	0.81
% Improvement i.e. (Rnew-Rold)/Rold %	17%	14%	-

Table 6.7 shows examples of trade mark scores of the original string phonetic similarity algorithm, i.e. ALINE, the edit distance and the proposed trade mark phonetic similarity algorithm. From the result shown in the table, it can be concluded that the proposed algorithm provides the greatest improvement for the pairs with typography symbols. This is as expected, as the algorithm includes a mechanism to extract phonological features of typography symbols, which initially not included and not applicable in the original ALINE algorithm. For example, the phonetic similarity computation for the trade mark pair "FERCREDIT" and "f@ir Credit" is made possible with the proposed algorithm and produced a 0.98 score.

The scores of the trade mark pairs with similar words and dissimilar arrangements have also improved, in line with the requirement guideline provided in the trade mark manual that indicates the similarity of the trade mark pairs under this condition. Such pairs from the table include "HEDGE INVEST"::"InvestHedge" and "SAT-COM"::"COM S.A.T.," both producing scores of 0.8. Similarly, for trade marks with spelling variations, such as "SWISS TALER"::"Svizze-rotaler," the algorithm has also improved their phonetic scores, especially those with similar beginning and ending letters.

Table 6.7 Examples of trade mark score improvements due to steps developed in the proposed algorithm

Trade Marks Comparison	Edit Distance	ALINE Algorithm	Proposed Algorithm
Hedge Invest :: InvestHedge	0.09	0.57	0.8
FERCREDIT :: f@ir Credit	0.80	NA	0.98
4US :: FOR US	0.40	NA	0.9
SAT-COM :: COM S.A.T	0.00	0.54	0.8
M24 :: N24	0.67	NA	0.96
TWIX :: TRIX	0.75	0.75	0.8
FEMARA :: Femagro	0.71	0.64	0.68
F 1: F ONE	0.25	NA	1
Preton :: PREBETON	0.75	0.77	0.82
VITS4KIDS :: KIDS VITS	0.44	NA	0.75
D&G :: DNG	0.67	NA	0.72
TIAMO :: TEA A MO	0.67	0.93	0.94
CH8888 :: 8888	0.67	NA	0.88
€08 :: Euro2008	0.25	NA	0.78
Frangelico :: FRAGOCELLO	0.50	0.58	0.67
SANTHERA :: SANZEZA	0.63	0.68	0.74
Viagra :: Viaguara	0.75	0.78	0.83
FENDI :: Flenddy	0.57	0.66	0.72
Prevista :: PREVISA	0.88	0.87	0.9
SWISS TALER :: Svizze-rotaler	0.50	0.67	0.74

6.4 Summary

Existing trade mark search systems utilises orthographic word similarity comparison, which is not suitable for phonetic comparisons. Furthermore, unlike other applications that require phonetic matching, trade marks also consist of typography symbols as part of their texts. This limitation, along with the phonological requirements of trade marks with typography symbols, has been successfully addressed in this study. The algorithm also fulfils the phonetic comparison requirement outlined in the manual for trade marks with identical constituents of words, but in different arrangements.

Secondly, the work presented in this chapter also provides a mechanism to compare and retrieve phonetically similar trade marks for useful application during the registration process to prevent future infringements. The similarity comparison scheme which has been design based on the trade mark manual allows automated examination which is applicable for a trade mark examination support system.

The evaluation performed on the proposed retrieval algorithm shows an improvement of 14% and 17% in comparison with the original ALINE algorithm and the edit distance algorithm, respectively. Typography mapping has enabled the phonetic computation of trade marks with symbols or special characters, and the token rearrangement developed in the algorithm improves the phonetic scores of the trade marks in line with the similarity guidelines provided in the manual.

The next chapter presents the aggregation algorithm that integrates the three aspects of trade mark comparison i.e. the visual, conceptual and phonetic similarities, for the computation of the overall trade mark degree of similarity.

Chapter 7

Trade Marks Degree of Similarity Aggregation

As defined at the beginning of this thesis, the main aim of this work is to develop an assessment support system for trade mark examination process during trade mark registration. The support system should be able to perform trade mark comparison analysis based on the three fundamental aspects of similarities and deduce the overall similarity. Since the line between similarity and dissimilarity is a very fine line, the concept of degree of similarity is thus introduced.

This chapter addresses the last research objective outlined in this thesis, which is to develop an aggregation method for trade mark degree of similarity computation. The chapter is organised as follows. Section 7.1 discusses the proposed trade mark degree of similarity aggregation method together with the fuzzy inference descriptions and justifications. Section 7.2, describes the experimental setup and evaluation method performed to evaluate the performance of the proposed algorithm, together with the results. The summary of this chapter is provided in Section 7.3.

7.1 Trade mark Degree of Similarity Aggregation Method

7.1.1 Justifications and Fuzzy Inference Description

An aggregation method using the three individual similarity aspects is proposed in this study based on the current practice that also performs trade mark assessment on the basis of global or overall similarity assessment. In addition to that, the concept of degree of similarity is normally used interchangeably during the assessment. Thus, an aggregation method is proposed in this study to aggregate the degree of similarity between trade marks. The proposed aggregation method is developed using a fuzzy inference model. Fuzzy based model is employed in this method based on the following reasons:

1. The database used in this study is extracted from real court cases of trade mark infringement which provides legal reports containing court decision together with descriptions by the experts on the degree of similarity between the trade marks involved in the disputes. The similarity descriptions are provided in natural language e.g. "there exist high similarity between trade mark A and B". Therefore, fuzzy inference approach is the best option that can be used to model trade mark similarity aggregation computation by the experts which practically described in natural language form. This is due to the capability of fuzzy logic that allow computation using words in which the objects of computation are drawn from natural language (Zadeh, 2001).

2. The trade mark similarity assessment is a process drawn from human judgement or human inference process. Fuzzy logic provides the mathematical modelling capability that can mimic the human thought and inference process (Bai and Wang, 2006).

3. In addition to that, trade mark similarity assessment is a standard procedure which involve legal aspect. Fuzzy approach has been recently used in a court cases decision-making study, which involved traffic violation (Sabahi and Akbarzadeh-T, 2014).

The steps involves in fuzzy inference approach generally consists of three main steps. They are the fuzzification, inference and defuzzification steps (Pappis and Siettos, 2005) .

1. Fuzzification is the process of transforming the crisp values to the linguistic terms of fuzzy sets i.e. very high, high, low and etc. through a set of membership functions (MF). The MF are various types of linear or non-linear shapes depending on the contexts and the modelled problem.

2. Inference is the fuzzy rule generation step i.e. the “if then “ rules, which consists of the antecedent and the consequence parts. The rules are generated based on the expert judgement or knowledge priori. The second part of inference step is the mapping from the fuzzy input to the fuzzy output using fuzzy composition such as the max-min composition (Jamshidi et al., 2013).

3. Defuzzification is the mapping process that maps the fuzzy sets into crisp value. The most popular defuzzifier method employed in literature is the centroid of area, which activates all the membership functions of the conclusions i.e. all active rules for the defuzzification process.

7.1.2 The proposed method

This section discusses the main steps involved in the proposed trade mark degree of similarity aggregation method which employs the steps involve in the fuzzy inference. It consists of four main steps, namely the similarity score computation and extraction, fuzzification, inference and defuzzification steps. A flow chart that graphically describes the proposed method is shown in Figure 7.1.

The description of the steps involved in this method is as follows:

1. **Visual, conceptual and phonetic similarity scores computation and extraction**

This step involves three similarity modules that embody the proposed method. The

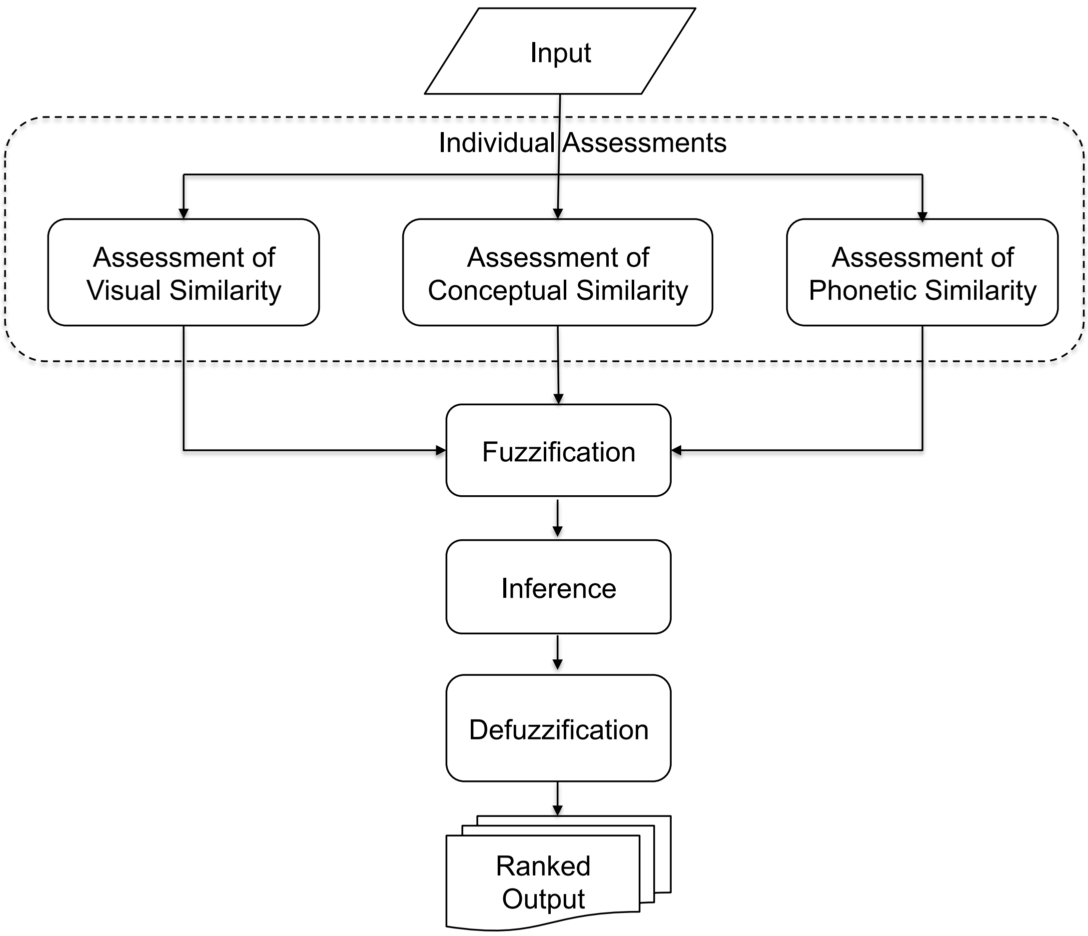


Figure 7.1 The flow chart of the proposed aggregation method

individual similarity score from each module is computed based on the algorithms presented in Chapter 4 (for visual similarity score of purely figurative trade marks i.e. based on integrated shape descriptors and trade mark with text element i.e. based on the individual shape of letters), Chapter 5 (for conceptual similarity score) and Chapter 6 (for phonetic similarity score). These scores are then normalised in the scale of [0-1] and used in the next step.

2. Fuzzification

A fuzziffication step is a transformation process that maps the individual similarity scores obtained in the previous step to fuzzy set values. In this method, the fuzzification step is performed on the three input variables i.e. the scores computed in the visual, conceptual and phonetic modules using a set of pre-defined membership functions per input variable.

Five triangular-based membership functions as defined in Equation 7.1, are employed. The triangular-based membership functions are used in this study due to their simplicity and previous performance, which have been proven theoretically in (Barua et al., 2014) and employed in many various engineering and non-engineering applications (Ngai and Wat, 2005, Gañán et al., 2012, Kaur and Kaur, 2012). Moreover, the functions have just also been recently used in a study for court cases decision-making study, which involved traffic violation and crime cases (Sabahi and Akbarzadeh-T, 2014). Therefore, the involvement of these functions across wide range of applications has made them applicable in the derivation of the proposed degree of similarity score aggregation method.

$$f_1(x) = \begin{cases} \dfrac{0.25 - x}{0.25}, & 0 \le x \le 0.25 \\ 0, & 0 \ge 0.25 \end{cases} \qquad f_2(x) = \begin{cases} 0, & x \le 0 \\ \dfrac{x}{0.25}, & 0 \le x \le 0.25 \\ \dfrac{0.5 - x}{0.25}, & 0.25 \le x \le 0.5 \\ 0, & x \ge 0.5 \end{cases}$$

$$f_3(x) = \begin{cases} 0, & x \le 0.25 \\ \dfrac{x - 0.25}{0.25}, & 0.25 \le x \le 0.5 \\ \dfrac{0.75 - x}{0.25}, & 0.5 \le x \le 0.75 \\ 0, & x \ge 0.75 \end{cases} \qquad f_4(x) = \begin{cases} 0, & x \le 0.5 \\ \dfrac{x - 0.5}{0.25}, & 0.5 \le x \le 0.75 \\ \dfrac{1 - x}{0.25}, & 0.75 \le x \le 1 \\ 0, & x \ge 1 \end{cases} \tag{7.1}$$

$$f_5(x) = \begin{cases} 0, & x \le 0.75 \\ \dfrac{x - 0.75}{0.25}, & 0.75 \le x \le 1 \end{cases}$$

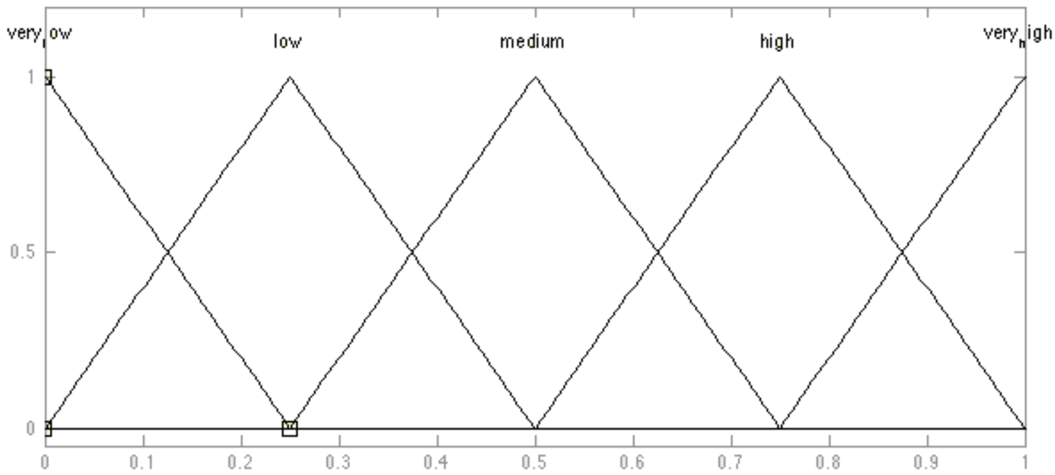


Figure 7.2 The input membership functions employed within Matlab Fuzzy Logic Toolbox

The set of membership functions defined in the method are applied to the three input variables used in this study and the graphical representation of the employed membership functions are shown in Figure 7.2, developed using Matlab Fuzzy Logic Toolbox.

3. Inference

An inference step is the process of invoking a set of fuzzy rules such that the appropriate rules are fired. The Mamdani fuzzy inference model is employed in this step to realize this process. The Mamdani model is a commonly used inference model in various fuzzy logic-based applications such as the ones in (Chatzichristofis et al., 2012, Abou and Saleh, 2011, Akgun et al., 2012). According to the model, a set of fuzzy rules is first developed based on the pre-defined knowledge-based information. In this study, the knowledge-based information is based on the guidelines in the trade mark examination manual (OHIM, 2012c) and an empirical study on the 1400 trade marks involved in dispute cases (Database-Court-Cases).

The fuzzy rules are then expressed in a tabular form, using five two-dimensional fuzzy associative matrices, which corresponds to a total of 125 rules altogether. The five associative matrices that represent the developed fuzzy rules are shown in Figure 7.3. Five inputs and outputs conditions are used to associate with each rules i.e. VL, L, M, H, VH, which correspond to very low, low, medium, high and very high scores. Each cell in the associative matrices corresponds to the consequence triggered by the rules associate with the antecedents of the input variables. For example, in the first cell of the matrix (c) in Figure 7.3, the fuzzy rule is translated as the statement shown in Figure 7.4.

PHONETIC V L		CONCEPTUAL				
		VL	L	M	H	VH
VISUAL	VL	VL	VL	L	H	VH
	L	VL	L	L	H	VH
	M	L	L	M	H	VH
	H	H	H	H	H	VH
	VH	VH	VH	VH	VH	VH

(a)

PHONETIC L		CONCEPTUAL				
		VL	L	M	H	VH
VISUAL	VL	VL	VL	L	H	VH
	L	VL	L	M	H	VH
	M	L	M	M	H	VH
	H	H	H	H	H	VH
	VH	VH	VH	VH	VH	VH

(b)

PHONETIC M		CONCEPTUAL				
		VL	L	M	H	VH
VISUAL	VL	L	M	M	H	VH
	L	M	M	M	H	VH
	M	M	M	M	H	VH
	H	H	H	H	H	VH
	VH	VH	VH	VH	VH	VH

(c)

PHONETIC H		CONCEPTUAL				
		VL	L	M	H	VH
VISUAL	VL	H	H	H	H	VH
	L	H	H	H	H	VH
	M	H	H	H	H	VH
	H	H	H	H	H	VH
	VH	VH	VH	VH	VH	VH

(d)

PHONETIC VH		CONCEPTUAL				
		VL	L	M	H	VH
VISUAL	VL	H	H	VH	VH	VH
	L	H	H	VH	VH	VH
	M	VH	VH	VH	VH	VH
	H	VH	VH	VH	VH	VH
	VH	VH	VH	VH	VH	VH

(e)

Figure 7.3 Associative matrices used for rules derivation in the in the inference process

IF the phonetic score **IS** M (medium) and the conceptual score **IS** VL (very low) and the visual score **IS** VL (very low), **THEN** the output score **IS** L (low)

Figure 7.4 Example of the fuzzy rule phrases employed in the inference process, which corresponds to the first cell from the matrix (c) in Figure 7.3

In addition to the fuzzy rules presented in the associative matrices, the inference step also requires a set of output membership functions for the output aggregation purpose. The output membership functions that represent the consequence part in the rule statements also consist of five triangular-based functions as in Equation. 7.2. The graphical representations of these functions are shown in Figure. 7.5.

After the derivation of each rule and their corresponding outputs, the second part of this step is to aggregate the compositional output. It involves fuzzy operation, between the fuzzified input and the fuzzy relations established by the rules. The compositional output in this step is thus derived using the implication-aggregation (min-max) compositional output (Akgun et al., 2012), and is defined as the following:

$$\mu_o = \max(\min(\mu_{i_1}(k), \mu_{i_2}(k), \mu_{i_3}(k)) \quad (7.3)$$

where $\boldsymbol{\mu_{i_1}}, \boldsymbol{\mu_{i_2}}, \boldsymbol{\mu_{i_3}}$ are the mapping of the first, second and third input from the crisp

$$f_1(x) = \begin{cases} \dfrac{0.2 - x}{0.3}, & 0 \le x \le 0.2 \\ 0, & 0 \ge 0.2 \end{cases} \qquad f_2(x) = \begin{cases} 0, & x \le 0 \\ \dfrac{x + 0.1}{0.3}, & 0 \le x \le 0.2 \\ \dfrac{0.5 - x}{0.3}, & 0.2 \le x \le 0.5 \\ 0, & x \ge 0.5 \end{cases}$$

$$f_3(x) = \begin{cases} 0, & x \le 0.2 \\ \dfrac{x - 0.2}{0.3}, & 0.2 \le x \le 0.5 \\ \dfrac{0.8 - x}{0.3}, & 0.5 \le x \le 0.8 \\ 0, & x \ge 0.8 \end{cases} \qquad f_4(x) = \begin{cases} 0, & x \le 0.5 \\ \dfrac{x - 0.5}{0.3}, & 0.5 \le x \le 0.8 \\ \dfrac{1.1 - x}{0.3}, & 0.8 \le x \le 1 \end{cases} \quad (7.2)$$

$$f_5(x) = \begin{cases} 0, & x \le 0.8 \\ \dfrac{x - 0.8}{0.3}, & 0.8 \le x \le 1 \end{cases}$$

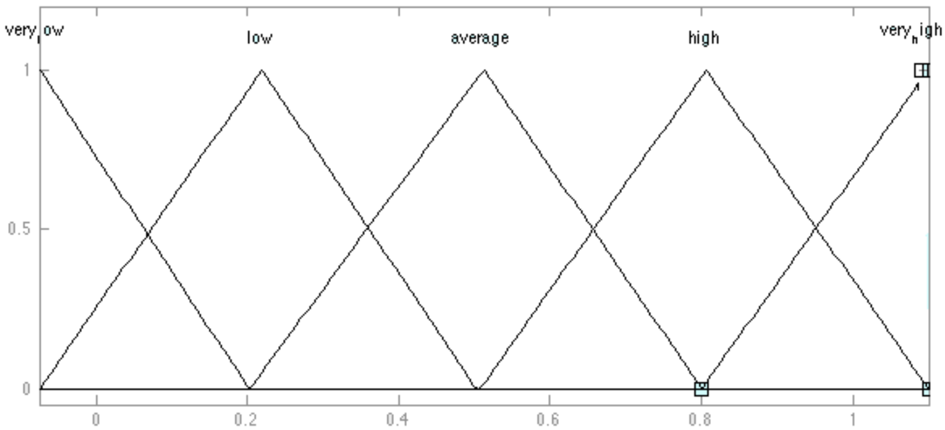


Figure 7.5 The output membership functions utilised in the inference process

set, i.e. the visual, conceptual and phonetic similarity scores, to the fuzzy set, and *k* is the *k-th* if-then preposition or the fuzzy rules.

4. Defuzzification

The defuzzification step employs the centroid or centre of mass defuzzification method to quantify the compositional output from the fuzzy set to the desired output that corresponds to the degree of similarity values. It computes the centroid under the curve, which resulted from the compositional operation performed during the inference step. The centroid computation is given by the following equation:

$$\text{centroid}=\frac{\int f(x)\cdot x d(x)}{\int f(x) d(x)} \tag{7.4}$$

where *f(x)* is the output functions associates with the compositional output. Figure 7.6 shows an illustrative example of the proposed aggregation method for trade mark pair Skypine and SKYLINE.

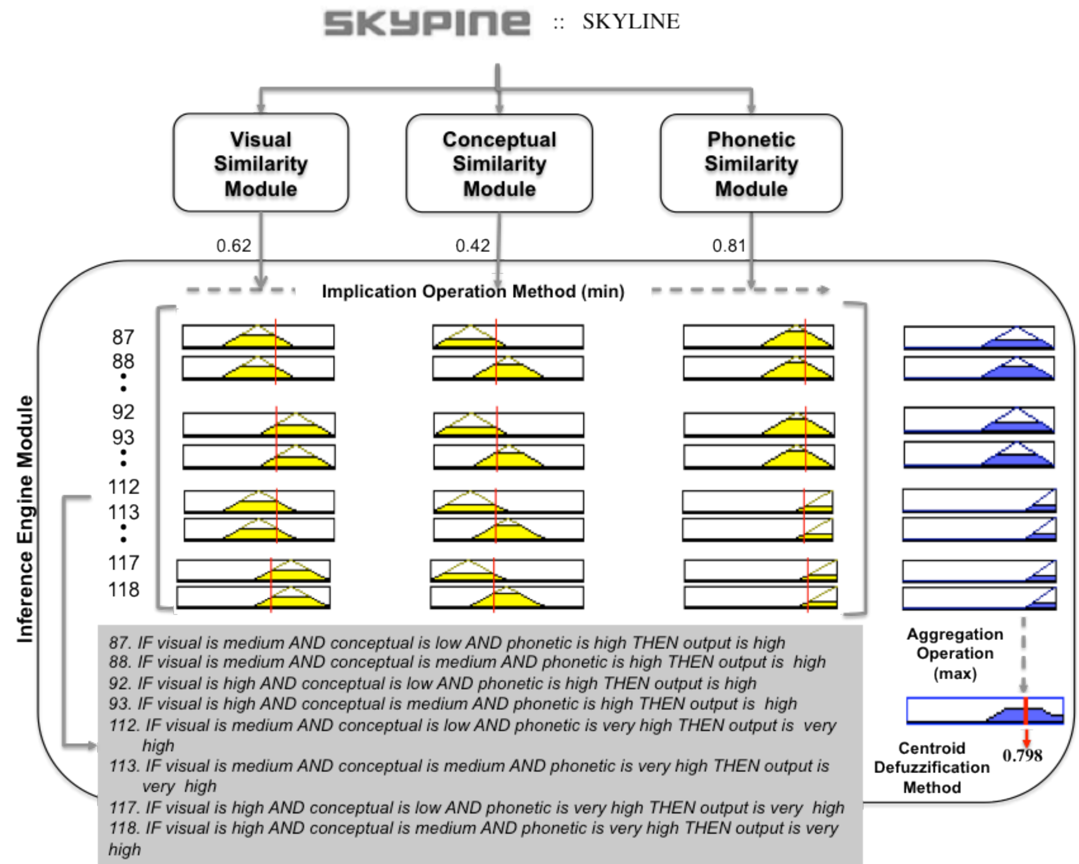


Figure 7.6 An illustrative example of the proposed aggregation method

7.2 Experimental Setup and Evaluation

7.2.1 Experimental Setup

Two experiments are then conducted in this study to evaluate the performance of the proposed aggregation method. Thus, this section describes the two experiments, together with the evaluation method employed.

Experiment 1

The main objective of the first experiment is to test the classification performance based on the trade mark degree of similarity scores obtained from the proposed method using information retrieval evaluation approach. The F-score, precision score and accuracy score are employed as the performance measures in this experiment. The scores are derived from a classification confusion matric as shown in Figure 7.7 where TP, FP, FN and TN are the true positive, false positive, false negative and true negative.

The database employed in this experiment is a collection of real court cases comprises 1,400 trade marks, a similar database used in chapter 5 and chapter 6 in this thesis. The decisions of the court cases together with the experts' remarks and

		Predicted Class	
		Positive	Negative
Actual Class	Positive	**TP**	**FN**
	Negative	**FP**	**TN**

Figure 7.7 The confusion matrix employed for the computation of the F-score, precision and accuracy scores

On the visual level, the trade marks have a strong similarity in the sense that the length of the verbal elements is almost identical (AURA / AUREA) i.e. four against five letters. Only the vowel "E" of the contested trade mark differs from the four letters of "AURA" trade mark. The overall visual impression is therefore very similar.
Aurally, the signs are also very similar. The vowel "E" can be easily used. The overall phonetic impression is also very similar.
Although that there is no conceptual similarity, the risk of misperception on trade marks does exist due to high visual and phonetic similarity.
The fact that the opponent has an additional letter 'E' does not change the overall similarity finding. In view of that, the similarity of the trademarks is therefore recognised.

Figure 7.8 An example from the real court case report (Database-Court-Cases)

comments in the legal reports are first analysed and studied. An excerpt example of a court case report between disputed trade marks i.e. AURA AND AUREA, is shown in Figure 7.8. The excerpt shown is part of the report that provides the expert findings on trade mark similarity for that particular dispute case. Based on similar findings, the database is then grouped into two groups (positive and negative classes).

For evaluation purposes, the database is then divided into training and testing set. The training set is used to obtain a threshold score to classify the data set employed in this experiment. Pairwise degrees of similarity scores between the trade mark pairs in the training set are first computed using the proposed method. A histogram-based algorithm (Nobuyuki, 1979) is then employed to estimate the threshold value on the computed degree of similarity scores by exhaustively searches for a value that minimizes the intra class variance of the binary classes.

The threshold estimation procedure is then repeated 1000 times on 1000 randomly selected training sets to find the optimal threshold value, T_{opt}. In this experiment, the acquired T_{opt}= 0.616. The pairwise degree of similarity scores between trade marks pairs in the testing set is then computed and the T_{opt} is used to classify the testing set into two classes. The F-score, precision and accuracy scores for the binary classification of the proposed method is computed using the following equations:

$$\text{F-score}=\frac{2TP}{TP+FP+TP+FN} \tag{7.5}$$

$$\text{precision}=\frac{TP}{TP+FP} \tag{7.6}$$

$$\text{accuracy}=\frac{TP+TN}{\text{Total Data}} \tag{7.7}$$

where *TP, TN, FP* and *FN* are the true positive, the true negative, the false positive and the false negative set of trade marks from the binary classification performed in this experiment and the *Total Data* is the total trade marks pairs in the database which amounting to a total of 700 pairs.

The procedure is then repeated using the scores derived from individual trade marks similarity aspects i.e. visual, conceptual and phonetic similarities. These individual scores are derived based on the algorithms presented in Chapter 4, Chapter 5 and Chapter 6 of this thesis.

Experiment 2

The main objective of this experiment is to measure the correlation between the degree of similarity scores produced by the proposed method against the similarity scores produced by human collective judgement. The rationale behind this experiment is to investigate whether the produced scores correlate with the way human perceive similarity. Therefore, two hypotheses are developed at the beginning of the experiment and they are as the following;

1. The ranking scores derived based on the proposed method does correlates with human collective judgment.
2. The rating scores derived based on the proposed method does also correlates with human collective judgment.

Two statistical significance tests are performed on the Spearman rank correlation score and the Pearson pairwise correlation score between trade mark similarity scores obtained from the proposed method and from the human collective judgment. The significance tests are conducted to statistically prove the derived hypotheses and reject the null hypotheses of this experiment.

Spearman rank correlation score, which takes values in the range of -1 to 1 (both -1 and 1 being the perfect negative and positive correlation and 0 being no correlation), is a measure of statistical dependence between two ranked variables. The score describes how strong the relationship between the ranked variable can be described using monotonic function. Pearson pairwise correlation score on the other hand, measures the strength of a linear association between two variables. In a nutshell, the Pearson correlation attempts to draw a line of best fit through the data of two variables, whilst the score itself describes the dispersion of the data points from the line of best fit. The Pearson correlation score also takes similar value range as the Spearman rank correlation score.

The human collective trade mark similarity judgments are collected using a Crowdsourcing platform. The Crowdsourcing is an open call task recently used in information retrieval study; and has been proven to produce fast and reliable results in a cost-effective way (Fadzli and Setchi, 2012, Snow et al., 2008, Corney et al., 2010). In Crowdsourcing, the task is sent to a large group of people known as workers to solve a problem or complete a task. This task, which commonly known as human intelligence task (HIT), is a small portion of an even larger task, distributed among a large group of workers, who apparently have no contact among them. Payment is made to the worker in exchange for completing the task upon HIT completion.

A total of 25 trade marks from the database used in the previous experiment are randomly selected as the query set in this experiment. Using the proposed aggregation method, each queries returns a set of trade mark list ranking from the highest degree of similarity score to the lowest score. From the retrieved set, 3 trade marks, each from high (ds>3.5), medium (2.0<ds<=3.5) and low (ds<=2.0) distribution scores are extracted and used for the Crowdsourcing task. Table 7.1 shows the 25 queries employed in this experiment together with the three retrieved results obtained using the proposed method. Result 1, Result 2 and Result 3 from the tables correspond to the retrieved trade marks that score high, medium and low similarity.

Figure 7.9 shows an example of the HIT designed in this experiment. In each HIT, three different trade marks are presented and the workers are required to rate the similarity scores between the query trade mark and the corresponding trade marks in the scale of 1 to 5 (1 being the least similar and 5 being the most similar). For each query, 20 different workers are assigned to rate the similarity scores, which amounting to a total of 500 HITs.

Table 7.1 The list of 25 queries and their corresponding results used in this experiment

Queries	Result 1	Result 2	Result 3
webautor	WEBIATOR	WebFOCUS	autoscout24
FRUIT TIGER	LION FRUIT	SMOOTH FRUIT	RED BULL
GSTAR	XSTAR	STAR FLEX	sakira
SVIZZEROTALER	SWISS TALER	SEVIKAR	SCHNEIDER
NEXT	NEST	Nexans	NR
SKYPINE	SKYLINE	SKY ROOM	DECOLINE
Prevista	PREVISA	ad-vista	BONITA
SWEETLAND	SUGARLAND	HEIDI LAND	SWISSOLAR
AMORA	AMORE	AXARA	ARTOR
RIMOSTIL	Rivotril	REBOVIR	REFODERM
CYRA	CYREL	ara	adria
GLOBRIX	Globix	ZYLORIC	GRILON
Lifestyle	Living Style	LIFE TEX	SNOW LIFE
WOOD STONE	MOONSTONE	WILTON	SwissTron
NUTELLA	NATURE ELLA	NATURESSA	MARQUELA
ecopower	ECOPOWER	GreenPower	HARRY POTTER
Twix	TRIX	TREAC	TREAKOL
SANTHERA	SANZEZA	SALFIRA	sunirse
MUROLINO	MURINO	MONARI	MATTERHORN
MAGIC TIMES	MAGIC HOUR	Maritimer	MATCH WORLD
RED BULL	BLUEBULL	FLYING BULL	A&A Bull and Bear
Feel'n LEARN	SEE'N LEARN	FEEL GOOD	FIGUREHEAD
bonvita	BONAVITA	biovital	Botoceutical
FMH	FNH	FTG	MR
ACTIVIA	ACTEVA	ADWISTA	ACCET

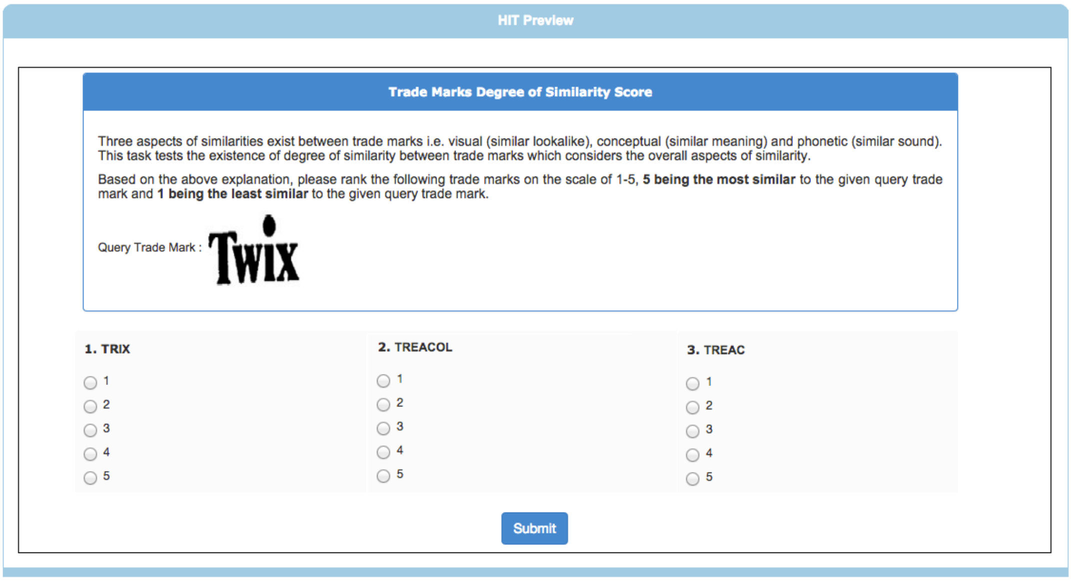


Figure 7.9 HIT example used in this experiment

The HITs workers are selected based on two criteria i.e. the number of their previously completed assignments and the acceptance rate of their previously completed assignments. The first criterion requires the workers to previously completed at least 1000 similar HITs. As for the second criterion, the acceptance rate of the previously completed HITs is sets to 95%, which means that at least 95% of the previously completed HITs had been approved and accepted by their HITs requestors. The criteria are designed such that only experienced workers with serious attitude are selected to work on the HITs, and thus ensuring that the collected feedback is of high quality. The average similarity scores of the 20 assigned workers in each queries and their respective results are then computed.

7.2.2 Result and Analysis

This section presents the results of the two experiment conducted in this study. It also discusses the analysis of the result obtained together with the improvement made by proposed method.

Experiment 1

The classification results from the first experiment using the scores derived from the proposed method against the three individual similarity scores is shown in Table 7.2. The result from the first experiment provides classification performance produced by the proposed method, which utilises all similarity aspects in trade marks in comparison to using only an individual aspect of similarity. For the result from the first measure examined in this experiment, i.e. the F-score, the proposed method produces an F-Score of 0.912, which translates to improvements of 15.2%, 150% and 12.6% as compared to the performance produced by the individual similarity aspects i.e. the visual, conceptual and phonetic similarity score,

Table 7.2 The F-scores, precision scores and accuracy scores using the similarity scores of the proposed algorithm and individual similarity scores i.e. visual, conceptual and phonetic

	Visual Similarity	Conceptual Similarity	Phonetic Similarity	Proposed Degree of Similarity
F-score	0.792	0.364	0.810	0.912
Precision	0.684	0.224	0.681	0.923
Accuracy	0.820	0.609	0.681	0.911

respectively. The F-score produced by the phonetic similarity score produced the best result among the three (an F-score of 0.810) whilst the conceptual similarity score shows the worst performance (an F-score of 0.364). In the domain of information retrieval, in particular the binary classification field, the F-score or also commonly known as F-measure, is considered one of accuracy measure which take into accounts both the precision and recall scores of the system. Therefore, it provides a more balance interpretation of the classification performance. The F-score attains its best value at 1.0 and worst value at 0.0, and with the score 0.912 produced by the proposed method, it can be deduced that the proposed method has achieved considerably good classification performance.

The second measure, i.e. the precision score, is a measure that reflects the capability of the method to correctly classify the predictive class. The score itself is the fraction of relevant retrieved items. In this experiment, the precision score produced by the proposed method also surpasses all the precision scores produced by each of the individual similarity aspects. At a precision score of 0.923, it has improved the individual performance of the visual, conceptual and phonetic similarity score by 35%, 312% and 33.7% consecutively. The result of the last measure from the first experiment i.e. the accuracy score also shows significant improvement by the proposed method. It produces an accuracy score of 0.911 as compared to 0.820, 0.609 and 0.681, produced by the individual visual, conceptual and phonetic similarity score, which provides a series of improvements of 11%, 49% and 33.7% respectively.

In general, the result from the first experiment has clearly proven that the proposed degree of similarity aggregation method produced the best classification performance relative to the performance produced using the individual similarity aspects. It therefore confirms that the combination of the three similarity scores using the proposed aggregation method, has improved the overall classification performance. Furthermore, the approach used in the method inline with the trade mark examination practice, which considers the three similarity aspects, arises between trade marks.

Experiment 2

The analysis of the results obtained from the second experiment seeks to investigate the performance of the proposed method in a slightly different perspective. It examines the performance of the method in comparison with human collective judgment and aims to prove that the similarity ranking and rating scores produced using the proposed method align or correlate with human judgment. Two correlation measures i.e. the Spearman rank correlation score and the Pearson pairwise correlation score are employed to statistically prove the hypotheses defined in this experiment.

The result of the second experiment is presented in Table 7.3. The scores of the 25 queries used in this experiment, which are derived based on the proposed aggregation method are then rescaled towards the scoring scale used in the HIT assignment and tabulated in the table together with the similarity scores from the Crowdsourcing exercise. A scattered plot of the similarity scores presented in this table is also shown in Figure 7.10. The similarity scores from Table 7.3 are also used to compute the Spearman rank correlation score and the Pearson pairwise correlation score, as shown in Table 7.4.

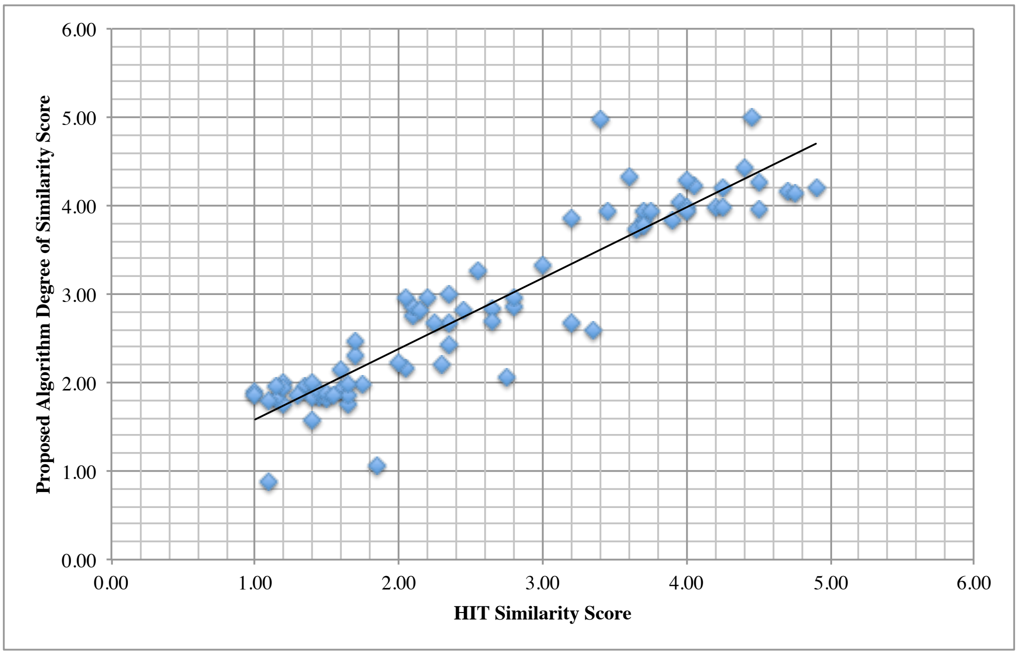


Figure 7.10 The scatter plot of the result presented in Table 7.3

Table 7.3 Similarity scores obtained from the HIT assignments and the proposed trade mark degree of similarity aggregation algorithm

No	QUERIES	Human Interactive Task Rating Scores			Proposed Algorithm Scores		
		Result 1	Result 2	Result 3	Result 1	Result 2	Result 3
1	webautor	3.40	2.35	1.00	4.98	2.99	1.90
2	FRUIT TIGER	3.45	2.05	1.20	3.94	2.17	1.75
3	GSTAR	4.05	2.45	1.00	4.23	2.82	1.86
4	SVIZZEROTALER	3.70	2.10	1.15	3.84	2.77	1.82
5	NEXT	4.00	2.80	1.10	4.29	2.86	1.79
6	SKYPINE	4.20	2.65	1.60	3.99	2.84	1.93
7	Prevista	4.70	3.20	1.35	4.17	2.68	1.96
8	SWEETLAND	3.70	2.10	1.20	3.94	2.85	2.00
9	AMORA	4.50	2.35	1.85	4.28	2.67	1.05
10	RIMOSTRIL	3.95	2.30	1.65	4.04	2.22	1.76
11	CYRA	3.75	2.25	1.45	3.94	2.68	1.83
12	GLOBRIX	4.75	1.60	1.40	4.14	2.14	1.84
13	Lifestyle	4.25	2.35	1.50	3.98	2.43	1.82
14	WOOD STONE	3.60	1.70	1.45	4.32	2.30	1.91
15	NUTELLA	3.65	2.20	1.40	3.74	2.96	2.00
16	ecopower	4.45	2.80	1.10	5.00	2.96	0.87
17	TWIX	4.00	1.70	1.20	3.98	2.48	1.94
18	SANTHERA	3.20	2.05	1.15	3.86	2.96	1.96
19	MUROLINO	4.50	3.35	1.65	3.97	2.59	1.85
20	MAGIC TIMES	3.70	2.15	1.50	3.78	2.82	1.88
21	RED BULL	3.90	3.00	1.75	3.85	3.33	1.98
22	Feel'n LEARN	4.00	2.55	1.30	3.95	3.28	1.85
23	bonvita	4.90	2.65	1.55	4.20	2.69	1.85
24	FMH	4.40	2.75	1.40	4.43	2.07	1.57
25	ACTIVIA	4.25	2.00	1.65	4.20	2.22	1.98
	Average	4.04	2.38	1.38	4.12	2.67	1.80

Table 7.4 The Spearman rank correlation score and the Pearson pairwise correlation score between the proposed aggregation method similarity score and the human interactive similarity score

Spearman Rank Correlation Score	Pearson Pairwise Correlation Score
1.00	0.92
($p < 0.05$ thus result is significance at 0.05)	($p < 0.0001$ thus result is significance at 0.05)

The result from Table 7.4 shows that proposed method obtains a perfect Spearman rank score of 1 and a Pearson pairwise correlation score of 0.92. Thus, the statistical significance test performed on both correlation scores has rejected the null hypotheses of the experiment and indirectly proves that the degree of similarity scores produced by the proposed algorithm correlates well with human collective judgment on assessing the trade mark overall similarity. The strong correlation can also be observed from the scatter graph shown in Figure 7.9. The graph displays the high concentration of almost all the points along the best-fit line (the straight black line on the graph).

7.3 Summary

The work presented in this chapter addresses the final objective in this study and is motivated by the realisation that, one of the factors that contribute to trade mark infringement, may be linked to similarities that arises between trade marks. Since trade mark similarities exist in three different aspects i.e. visual, conceptual and phonetic, a support system to assess the overall degree of similarity between trade marks is highly essential as a mean of trade mark protection.

The proposed method contributes to the field of trade mark retrieval research domain by proposing an aggregation method that incorporates the three aspects of similarities i.e. visual, conceptual phonetic. The method brings forward a new similarity comparison concept in trade mark retrieval analysis, by also utilising an inference engine developed using fuzzy logic. The proposed method is evaluated not only using information retrieval measures but also considers human collective judgment using Crowdsourcing platform. The results from both experiment performed in this study conclude that there is a significant improvement in trade mark similarity assessment when utilising all similarity aspects arises between trade marks and the generated ranking scores using the proposed method correlates well with human collective judgment.

Chapter 8

Conclusions

This chapter concludes the work presented in this thesis. Section 8.1 lists the main contributions of this research. Section 8.2 provides the conclusions; the directions of future work are discussed in Section 8.3.

8.1 Contributions

The contributions of this study are as follows:

i. A conceptual model of a trade mark similarity assessment support system is proposed and developed. The model integrates the three fundamental aspects of trade mark similarity i.e. the visual, conceptual and phonetic, together with an inference engine for aggregating the trade marks degree of similarity score;

ii. A retrieval algorithm based on visual similarity for figurative trade mark is proposed, which utilises shape-based feature descriptor and a feature matching strategy. The proposed algorithm enhances the shape feature representation of the trade mark by incorporating global and local features. The developed shape feature descriptors are also used for visual comparison of trade mark with text element;

iii. A semantic trade mark retrieval algorithm is proposed. The algorithm utilises external knowledge sources and a lexical ontology, WordNet. It advances the state of the art in the field by providing a mechanism to compare trade marks based on their conceptual similarity;

iv. An algorithm to phonetically compare and retrieve trade mark is proposed. It employs a string phonetic algorithm, which uses phonological-based features in the trade mark similarity score computation. In addition, the algorithm also provides a mechanism to phonetically compare those trade marks with typographic characters;

v. A computational method to aggregate trade mark degree of similarity is proposed. The method is developed using a fuzzy-based inference model, which blends together the three fundamental aspects of trade mark similarity.

8.2 Conclusions

The main aim of this study is to develop a decision support system, which compares trade marks using their visual, textual and semantic similarity. In this thesis, the main aim together with the individual research objectives have been achieved.

The development of a conceptual model of a trade mark similarity assessment support system, which forms a fundamental framework of the system is designed based on the three aspects of trade mark comparison i.e. the visual, conceptual and phonetic similarities, requirement and processes, as outlined in the trade mark manual (OHIM, 2012c). The model, which provides an overview of the processing approach and technology employed, such as content-based image retrieval technology, semantic technology, natural language processing and phonological-based analysis, integrates the three similarity aspects using a fuzzy-based inference approach to aggregates the overall similarity score.

The visual retrieval and comparison of trade marks is performed using a novel integrated shape feature descriptor and a feature matching strategy. The proposed algorithm demonstrates an improved performance over state-of-the-art algorithms for figurative trade mark image retrieval. The algorithm employs the Zernike moments as the global descriptor and the edge-gradient co-occurrence matrix as the local descriptor. For trade marks with text element such as word mark and figurative word mark, the visual comparison is performed using the integrated shape feature descriptor together with a string alignment algorithm. Pairwise letter-to-letter visual comparison is performed using the developed visual shape descriptors. The algorithm is then compared with the approximate string technique i.e. a commonly used technique for string comparison, via visual inspection and found to provide better and more adequate visual similarity scores.

The proposed algorithm that semantically compares trade marks, has brought forward an entirely new similarity comparison concept in the domain of trade mark retrieval. It utilises natural language processing techniques, together with an external knowledge source in the form of a lexical ontology, i.e. WordNet. The evaluation using both information retrieval measures and human judgment shows a significant improvement, as the algorithm provides better results than the traditional baseline technique. The algorithm is not limited to the use of a specific word measure. This advantage provides flexibility to choose any word measure suitable for specific applications or requirements. Two sets of features are used to represent each trade mark, which are the token set feature and the synonyms set feature. The token feature set consists of a set of words that constitutes a trade mark. The synonyms feature set on the other hand is a set of synonyms that belongs to the trade mark tokens. The similarity score is then derived based on the set similarity theory i.e. Tversky contrast theory, which considers the number of shared features between the trade marks.

The phonetic similarity assessment on the other hand computes trade mark similarity based on the phonological feature of phonemes that constitutes the trade mark text. This algorithm uses a phonology-based string similarity algorithm together with typographic mapping and a token rearrangement process to compute phonetic similarity between trade marks The phonology-based string similarity algorithm represents phonemes from a word string as vectors with phonetic features where each vector consists of binary main features and multi-valued features extracted from the phonological properties of human speech production. Furthermore, unlike other applications that require phonetic matching, trade marks also consist of typography symbols as part of their texts. Hence, the developed phonetic similarity algorithm also performed a typography-mapping process, which converts special characters or symbols in the trade mark text to their corresponding meaning. The algorithm also fulfils the phonetic comparison requirement outlined in the manual for trade marks with similar constituents of words, but in different arrangements.

The computational method proposed in Chapter 7 in this thesis, advances the state-of-the-art in trade mark retrieval research domain by proposing an aggregation methodology that incorporates the three aspects of similarities i.e. visual, conceptual phonetic. The method brings forward an entirely new similarity comparison concept in trade mark retrieval analysis, by also utilising an inference engine developed using fuzzy logic. The proposed method is evaluated not only using information retrieval measures but also human collective judgment to show the significance of the proposed algorithm. The results from the experiment performed in this study confirm that there is a significant improvement in trade mark similarity assessment when utilising all similarity aspects of trade marks. In addition, the correlation results also support the original hypotheses outlined in this study.

In conclusions, the potential benefits provided by the proposed support system are threefold. The similarity comparison developed by the system, which covers the three compulsory aspects, addresses the trade mark similarity examination requirement and therefore improves the overall search quality. In addition to that, the proposed system provides another dimension to the trade mark comparison analysis in which trade mark search based on the overall similarity that encompasses the three fundamental aspects is also made possible in the analysis. Secondly, the proposed support system can be viewed as a trade mark infringement protection mean, which can potentially save future lost in terms of cost and also brand reputation for existing trade mark owners. Finally, the support system can also potentially reduce the trade mark registration time by providing a more robust and better quality trade mark search, which therefore reduces the probability of dealing with potential opposition cases during registration process.

8.3 Future work

The following is a list of potential work that can be considered in the future:

- The test to prove infringement, i.e. the likelihood of confusion test, involves several interdependence factors, one of which has been the focus of the work established in this thesis, which is the similarity between trade marks. Other interdependence factors include the similarity of goods and services, the similarity of the marketing channel, the strength of the trade marks and the evidence of actual confusion. Therefore, a future study that considers other interdependence factors that contribute to the likelihood of confusion can be considered. In addition, the prototype of the system developed in this study has an extendable structure, which will enable the integration of other factors into the system.

- The scope of the study presented in this thesis is trade mark similarity as it relates to word marks, figurative marks and figurative word marks. In the future, a similar study on other types of trade marks, such as three-dimensional figurative marks, colour marks and sound marks, should also be considered. For example a similarity comparison of colour marks may consider the low-level feature, i.e. the colour feature in CBIR studies, and a similarity comparison of sound marks may require audio low-level features as employed in content-based audio retrieval (CBAR).

- The figurative trade mark visual similarity comparison algorithm developed in this work focuses on two-dimensional figurative trade marks. However, an actual product or its packaging is also considered to be a trade mark that can be protected, i.e. a 3D mark, which can be represented using a three-dimensional shape. Hence, the visual similarity comparison algorithm established in this study can also be extended to three-dimensional figurative trade marks in the future.

- The conceptual similarity algorithm proposed in this study focuses on short phrases that contain multiple numbers of words. The algorithm is also applicable for retrieval applications, such as semantic retrieval of tagged images. Hence, the algorithm can also be extended to those types of retrieval applications.

- Finally, the phonetic algorithm developed in this study can also be extended to and made applicable for spell checking applications. The phonological features employed in the algorithm provide more scientific justification, which would be beneficial for those types of applications.

Appendix A

Experimental Data (samples)

This appendix provides samples of datasets used in the study presented in the thesis.

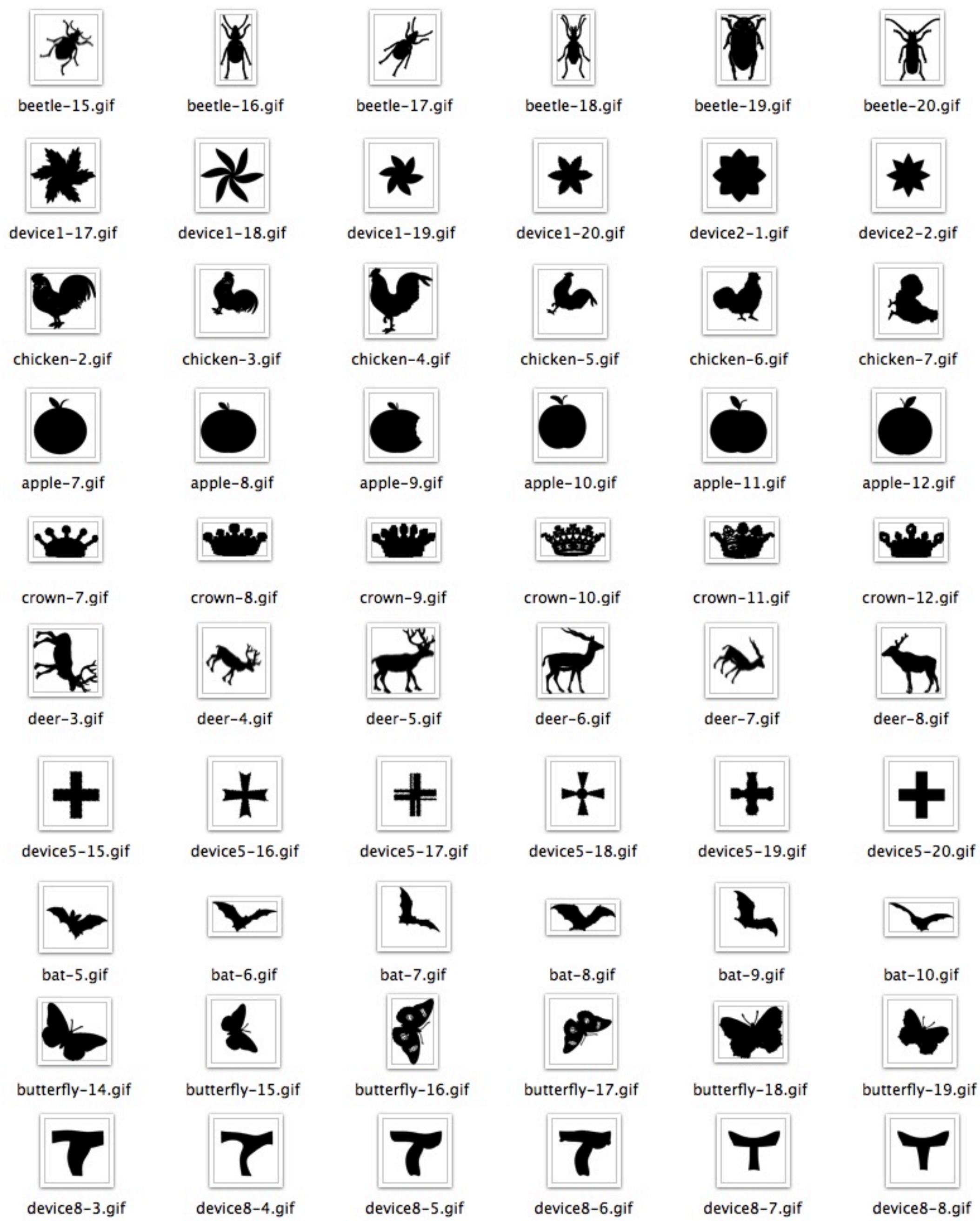


Figure A-1 The MPEG7 shape dataset (samples)

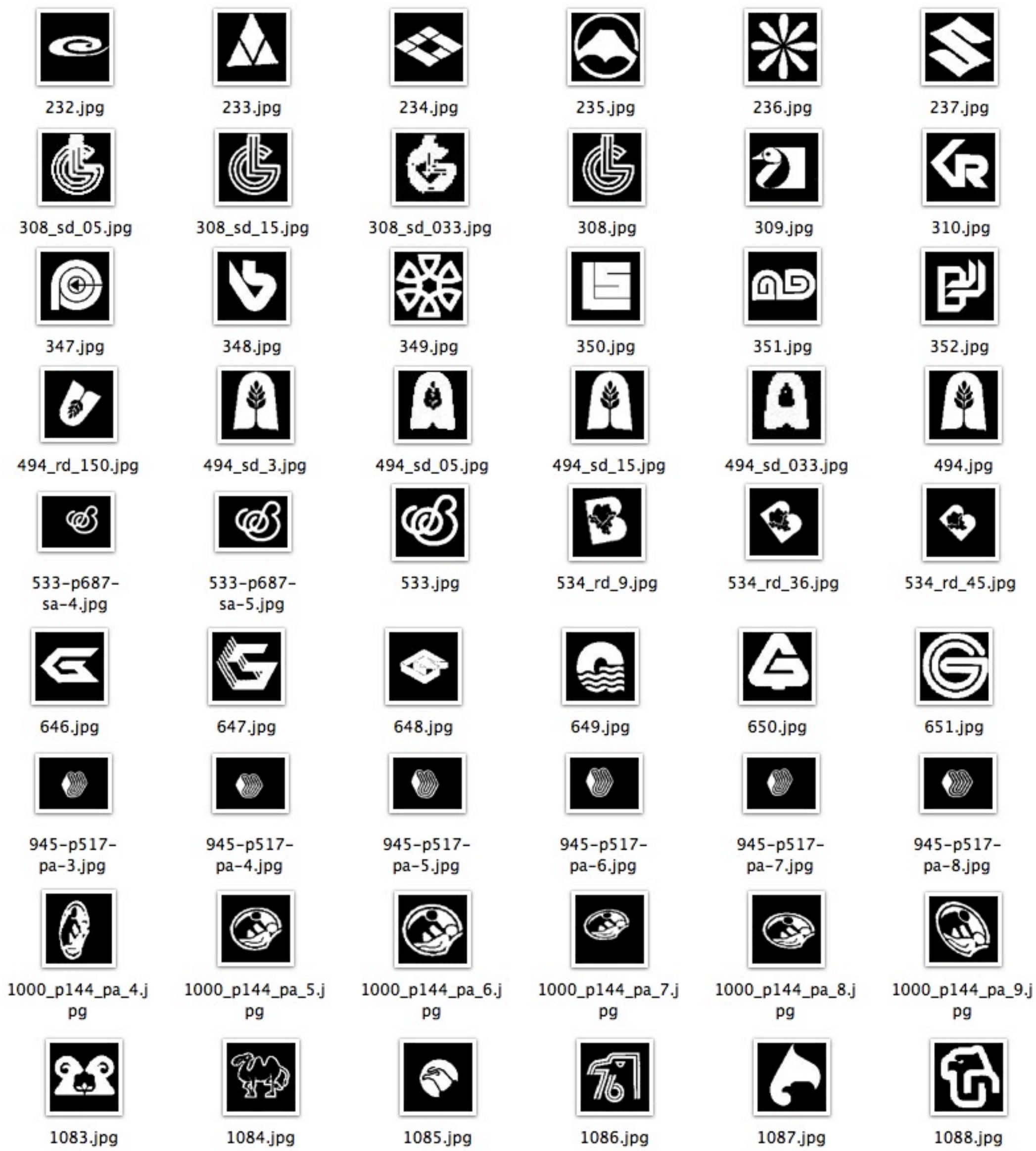


Figure A-2 The MPEG7 trade mark dataset (samples)

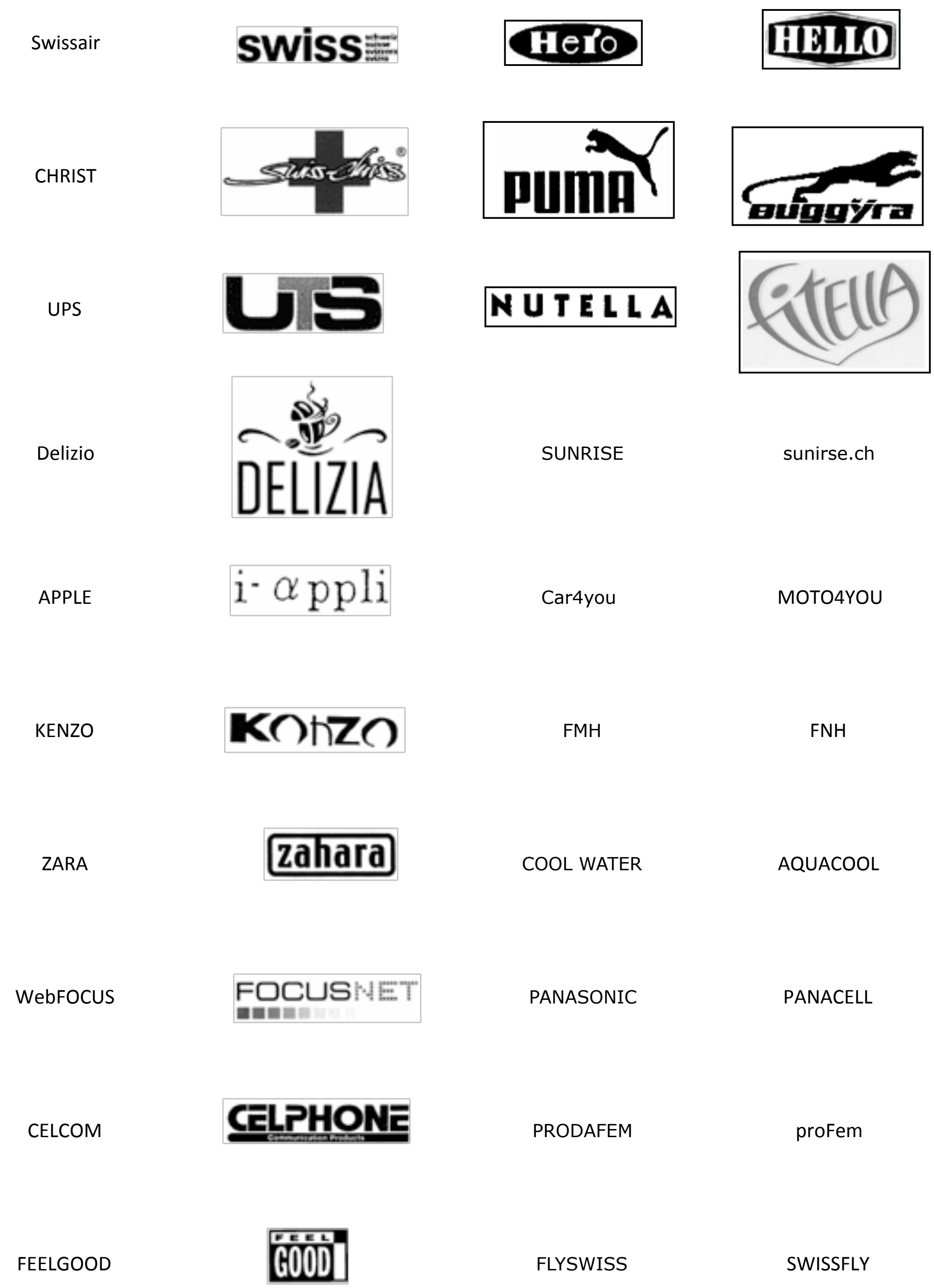


Figure A-3 The real court cases trade mark dataset (samples)

TMList.csv — Edited

```
[Recycling Engineering & Development Ltd]
[Red & Blue Ltd]
[Red Alert]
[Red Box Supplies]
[Red Brick Communications]
[Red Bull]
[Red Bus Recording Studios Ltd]
[Red Chili International Ltd]
[Red Cloud]
[Red Commerce Ltd]
[Red Cover Ltd]
[Red Cow Creative Ltd]
[Red Cow Hotel]
[Red Creative]
[Red Creators Marketing Solutions]
[Red Door Design]
[Red Door Ltd]
[Red Dragon Fm & Capital Gold]
[Red Education]
[Red Eye Display Graphics]
[Red Eye International Ltd]
[Red Eye International;ltd]
[Red Eye Records]
[Red Forge Ltd]
[Red Fox]
[Red Fox Media]
[Red Hot Events]
[Red Hot Publishing]
[Red Hot Vending]
[Red House Books Ltd]
[Red House Computers]
[Red House Day Nursery]
[Red House Hotel]
[Red House Ventures]
[Red Jacket]
[Red Ledge Ltd]
[Red Letter Days]
[Red Letter Design]
[Red Letter Media Consultants]
[Red Lightning Records]
[Red Lion Antiques]
[Red Lion Books]
[Red Lion UK]
[Red Loft Partnership]
[Red Logic]
[Red Logic Ltd]
[Red Lorry Yellow Lorry Ltd]
[Red Mosquito]
[Red Mullet]
```

Figure A-4 The company names dataset (samples)

Appendix B

Conceptual Similarity Crowdsourcing Evaluation: Experiment 1 Results

This appendix provides sample results of 10 queries from the human collective opinion experiment conducted on Amazon Mechanical Turk service to evaluate the performance of the proposed conceptual similarity comparison algorithm described in Chapter 5. The HIT assignment used in the experiment is as in Figure 5.8 (page 105). The sample results in this appendix correspond to the following HITs.

HIT NO	Queries	Option 1	Option 2	Option 3
1	Red Bull	The Red Cow	The Red Lion	Red Cover Ltd
2	PC AID	Pc Help Centre	Computer Aid	PC Support Ltd
3	Magic Kingdom	Magic City	Magic Man	Dance Kingdom
4	Bag & Baggage Ltd	Suitcases & Bags	Bag N Box	Premier Luggage & Bags Ltd
5	Pet Pillow	Pets At Rest	Pet Pad	The Pet Place
6	Star Ballroom	Star room	Superior Ballroom Pty Ltd	Planet Ballroom
7	First Ideas	First Concept	An Original Idea	First View
8	Gold Line	Goldprint	Silver Line Ltd	Gold Air International
9	Global Internet Ltd	Global Network Solutions	Global Web Ltd	Global Radio
10	Sushi Kingdom	The Sushi Place	Rock Candy Kingdom	Sushi World

Table B-1 The HITs queries and options used in the Crowdsourcing experiment, which correspond to the results provided in this appendix

HITId	AssignmentId	WorkerId	Worker Preferences
HIT 1	2ABG5TYMNCWYHCRPZ1JSRX11YEONJ0	A13T61GJTR2Y9B	Option1|Option2
	2JRJMJUNU8LZCZPA6EI9ID8JILE1H0	A198SS8SV0LWKB	Option1|Option2
	2RX7DZKPFE4EMLZNCBWLII9NEM65FO	A1MHGD46DB5Z7H	Option1
	2GK8SV7WGKCC1T3D2JU3WHAP5T9R1I	A22XK2FSFIAAFG	Option1|Option2
	2BUA1QP6AUC2CLYGXMSXDV0FZPB70Y	A233ONYNWKDIYF	Option1
	21DPHIT3HVWA1S0GSWAQC172EZ9CK5	A2FUPODRRCESB	Option1
	2PB51Y7QEOZF4YAB21KMYFXRSH2GD2	A2HM35CWB7IIFM	Option1
	2MTPC6SK9RJ8BWHSPN8MKAPM3DPR3C	A2JH6SJZDJHZ9I	Option1|Option2
	20SJG5TYMNCW4JMJ5IJS2HX1G8NIMF	A2M3KQ9CKP7YW	Option1
	2OJSQV66RLPHO1LRL51VUI6229QD5L	A2MCI9K0K5VX50	Option1
	25B8EBDPGFL61K76PIINNWIOARSH2X	A2QLSHXNCHBRN4	Option2
	2I3727M0IGFKNLJGOOJVP4VI3JXEZI	A2UX7ZJEGGU5	Option1
	22TCSTMOFXRDYC0MRNPDXXJF1QYQTP	A323WW03VM8089	Option1
	2U91Q6SVQ8H8EU84WUWOLVCIGHXN48	A37WXDYYT7RCZ0	Option1|Option2
	2EAXKO2L92HEI4SGNCPOMCF0RF6EFZ	A3E8SXH0BAYG85	Option1
	2DI0JG5TYMNC26TEZO0S2SHXGRJHLM	A3G3G7SCD88G1J	Option1|Option2
	2BIP6AUC26DGCFVBNCM0PK0C3A23AJ	A3O81LHBBI8NPK	Option1|Option2
	2F73Q0JG5TYMTKE81D0FJSSSWN1JFO	AFB9N61OMZXCX	Option1
	2HW6OQ1SNQQ7WEPAVAHKMNR1HJQQ6J	AO3XB5I5QNNUI	Option2
	226IUUU00OQKQIMS81ZSCU26NQFUUV	AOOJY0XKNYJYZ	Option1
HIT 2	2O41PC6SK9RJED69885HWAAP1EPQ23	A13T61GJTR2Y9B	Option1|Option2|Option3
	20KCM6IAA2SEO2C4Q9FQUKA4X7RLLU	A198SS8SV0LWKB	Option2
	2N9JHP4BDDKGA6Q1I60XDG35MMC6ZU	A1FQGVP8SX5WE2	Option1|Option2|Option3
	27CO2L92HECWGEFDOX3CP0CPKAXGHF	A1MHGD46DB5Z7H	Option1|Option2|Option3
	27P2Q45UUKQO4O5SMAESIOG0GP4UCF	A22XK2FSFIAAFG	Option2
	2LFFSVGULF39B0EGDPSF23NY28AN91	A233ONYNWKDIYF	Option1|Option2|Option3
	22CMT6YTWX4H9PKZ1D49JGI6X9R1W0	A2FUPODRRCESB	Option1|Option2
	2C5IPDOBDDP8VREUKM487MB35S81CO	A2HM35CWB7IIFM	Option1|Option2|Option3
	26CUDD8XMB3Q9HHA1FLTY6T4TLSPEC	A2JH6SJZDJHZ9I	Option1|Option2
	2FPH0JPPSI2K4M7VIYY5ULM6B82IOU	A2M3KQ9CKP7YW	Option1|Option2|Option3
	2VHHIT3HVWAVQQOCDSH2B72ZOZQDL9	A2MCI9K0K5VX50	Option2
	2Z8SNTL0XULRMVBL9CDMNX5F4XN1N9	A2QLSHXNCHBRN4	Option1|Option2|Option3
	2H51X3V0FK0CUSKT4AD7ZKK90HWMFV	A323WW03VM8089	Option1|Option2|Option3
	25IVJ8EBDPGFREDMF5Q91NDWXEVF0D	A37WXDYYT7RCZ0	Option2
	21Z0G5R98D8J93WHM1JTXYCGICCTDS	A3E8SXH0BAYG85	Option1|Option2|Option3
	22KCXKNQY2RCPSODP453RR0K98A1QW	A3G3G7SCD88G1J	Option1|Option2|Option3
	2UQEPLSP75KLSEETTX1H0EQVYG3YSD	A3O81LHBBI8NPK	Option2
	2ZV6XBAT2D5NW65F5CH0TG5TDCO51O	AFB9N61OMZXCX	Option1|Option2|Option3
	2F3MJTUHYW2GZXR10GJ56M16ONROJC	AO3XB5I5QNNUI	Option2
	2QXTYMNCWYB4FNR2I18XB1JO2IUPL0	AOOJY0XKNYJYZ	Option1|Option2|Option3

HITId	AssignmentId	WorkerId	Worker Preferences
HIT 3	2K6SCWY2AOO2MU4O6XFG0SCML8B221	A13T61GJTR2Y9B	Option1
	2U4J011K274JDH20MFS8X46UC4BDBJ	A198SS8SV0LWKB	Option1
	2ORZ2MIKMN9UEXR8THKW6XI37KZQ9V	A1FQGVP8SX5WE2	Option1
	2T0EBDPGFL6VIXE9Z0ED6IOVGI83IO	A1MHGD46DB5Z7H	Option1
	2QFTBJ3MMDX5LXPXWBBHL9MDCDGCYW	A22XK2FSFIAAFG	Option1
	24426DG67D1X93IPA93OU2JEGB6F8X	A233ONYNWKDIYF	Option1
	2XLL0XULRGNTHRLWCMO5PP7NLSK4QC	A2FUPODRRCESB	Option1
	22RVXX2Q45UUQY686W9WBNS835Z9RB	A2HM35CWB7IIFM	Option1
	28O2GTP9RA7SB44BWIPSYF70YBGQV7	A2M3KQ9CKP7YW	Option1
	21JLFQ0ONNVRN92REI5G1B762L9TK5	A2MCI9K0K5VX50	Option1
	2V12HECWA6X34WUM593PFKXP88OLKV	A2QD7QFGCUNF5N	Option1
	29BMJUNU8LZ6XFIQV008N8J3A36I2O	A2QLSHXNCHBRN4	Option1
	2EUJ1LY58B72DUIS6OBHN16YUHTS75	A323WW03VM8089	Option1
	2LSHFL42J1LYBGTHSGD0SGFKW31N2C	A37WXDYYT7RCZ0	Option1
	2E70OHOVR14I3S6CBITHOCWALN356L	A3E8SXH0BAYG85	Option1
	28FJ92NJKM05HU13KQPWCGTPOHAE96	A3G3G7SCD88G1J	Option1
	2M8J2D21O3W53PITFYJICKYE4BSE8H	A3O81LHBBI8NPK	Option1
	2RN8ER9Y8TNKOUH2CEBFRS2O1QQT61	AFB9N61OMZXCX	Option1
	2BUA1QP6AUC2CLYGXMSXDV0FZQC701	AO3XB5I5QNNUI	Option1
	2MHWZ9RNDWIO19AHIWUD3GU1IODTEL	AOOJY0XKNYJYZ	Option1
HIT 4	2RX7DZKPFE4EMLZNCBWLII9NEM7F5Z	A13T61GJTR2Y9B	Option1
	2C21QP6AUC26JOOH3AO350FKF1N81P	A198SS8SV0LWKB	Option2|Option3
	25CCJ011K274PFRUG5X1IN469NGACP	A1FQGVP8SX5WE2	Option1|Option3
	2GMFBNFSVGULLBRFI5XNQ1FSIDZ6K8	A1MHGD46DB5Z7H	Option1|Option3
	223RI8IUB2YUFG1RI2CBDL0FQ87I64	A22XK2FSFIAAFG	Option2
	2DPUYT3DHJHPAJVNAPVYIRSXON30T6	A233ONYNWKDIYF	Option1
	2ABPPSI2KYEPR07HVTCMGWJ33ZGLRK	A2FUPODRRCESB	Option1|Option2|Option3
	23VHVWAVKI62TR8CRGTZJ9QHL0JHPH	A2HM35CWB7IIFM	Option1|Option3
	2S0IUB2YU98JN0BV1CC0PBJ9XEBL90	A2JH6SJZDJHZ9I	Option1|Option3
	2UUJE1M7PKK9RZEGE81CA4LZCEKYRP	A2M3KQ9CKP7YW	Option1|Option3
	2TEJUNU8LZ6RD8YFHIZDIJ3VTXX3J0	A2MCI9K0K5VX50	Option1|Option2|Option3
	2YC2JE1M7PKKFT96WXQAM04LEMOQXA	A2QLSHXNCHBRN4	Option1|Option3
	2H5ZKPFE4EGDNL4CVUZIJNZWL6D7H0	A323WW03VM8089	Option1|Option3
	2Y1Z6KW4ZMAZNP91BOH0YNNV660G7A	A37WXDYYT7RCZ0	Option1|Option3
	224XKNQY2RCJQEL9LNUH10KUX0Q2RF	A3E8SXH0BAYG85	Option1|Option2|Option3
	26KBRI8IUB2Y0HQT71KLL3L0U0I5HJ	A3G3G7SCD88G1J	Option1|Option3
	262VKI62NJQ27FK9ZIHHGBKLRKDTL5	A3O81LHBBI8NPK	Option1
	2C8TP9RA7S5WS9OJO1FFH0JMWBBSX5	AFB9N61OMZXCX	Option1|Option2|Option3
	2CWSMEZZ2MIKSVR4YY0YD8TWBMHM59	AO3XB5I5QNNUI	Option1|Option2|Option3
	2O8OOGQSCM6IGIK24RLU400O5AKGGG	AOOJY0XKNYJYZ	Option1|Option2|Option3

HITId	AssignmentId	WorkerId	Worker Preferences
HIT 5	2FD8I9NZW6HE5E6OUZN73869VKMWM3	A13T61GJTR2Y9B	Option2
	27MYT3DHJHP4HLVU6DP81SX9CTG1U1	A198SS8SV0LWKB	Option2
	25GK5UFJ51Y7WM6957HSBCST1EFB8E	A1MHGD46DB5Z7H	Option2
	2MPKNQY2RCJKCBH54C8RAKUIPF7S30	A22XK2FSFIAAFG	Option2
	20V9Z0B6UTO6ZCW5I2MRUGPW7L3ZO7	A233ONYNWKDIYF	Option2
	297YQS1CSTMOL59NID9CBEYD2NJMPY	A2FUPODRRCESB	Option2
	2Y3DDP8PJWKUJLQ7CKUQD9Z0QVTH6B	A2HM35CWB7IIFM	Option2
	20ZQ67051QKCTZJCJZ317MGIFLEFZ5	A2JH6SJZDJHZ9I	Option2
	28XCOW0LGRZ3EK9PBLXVXUZWSG0Z85	A2M3KQ9CKP7YW	Option2
	2VQHVI44OS2KR2QNDNQSLAP5QR15ZD	A2MCI9K0K5VX50	Option1|Option2
	2YFNVRH1KHO9KO9LXFEVJLKWMMLZQF	A2QLSHXNCHBRN4	Option1|Option2
	2BKNQQ7Q67057Y2MD0S23QC1CBEVBZ	A323WW03VM8089	Option2
	26W0SPW1INMHM68E9CEAL6BF14EG35	A37WXDYYT7RCZ0	Option1|Option2
	2LDYHVI44OS2QTCI3W5Z2BAPK114YF	A3E8SXH0BAYG85	Option2
	22NQ8H88MQU6RD6LLL911XX4P8J9S2	A3G3G7SCD88G1J	Option2
	2Y91XERSQV66XT7R82UH5WAVZ8691I	A3O81LHBBI8NPK	Option2
	2QFTBJ3MMDX5LXPXWBBHL9MDCEICY0	A3RLCGRXA34GC0	Option1|Option2
	29CPFE4EGDHDSANVYR0N9W6HTP79JN	AFB9N61OMZXCX	Option1|Option2
	29NXX2Q45UUKWWGQDRN1XS8OVP0ASF	AO3XB5I5QNNUI	Option2
	2G2UC26DG67D75L5QOB0MOK2Y426DV	AOOJY0XKNYJYZ	Option2
HIT 5	2QGOGQSCM6IAGAAO83LUA0OQZAAHHF	A198SS8SV0LWKB	Option1|Option3
	2A85R98D8J3VKFE2I2EYMG3MRA9VFM	A1FQGVP8SX5WE2	Option1|Option3
	2DQOCCF0CP5K3XBSDR9X8G4P1XNVUK	A1MHGD46DB5Z7H	Option1
	29YR70G5R98DERL54GNS2TNYR50RB1	A22XK2FSFIAAFG	Option1|Option3
	26NOX7H57DZKVNWE4P4HNM250XHA0S	A233ONYNWKDIYF	Option2
	2HOGKCCVLL3CGBLW7JGQEC9N5K76W3	A2FUPODRRCESB	Option1|Option3
	2GJ70G5R98D8PBDOX5JS3NYCVSLCSJ	A2HM35CWB7IIFM	Option2|Option3
	226IUUU00OQKQIMS81ZSCU26NQEUUU	A2JH6SJZDJHZ9I	Option1|Option3
	2HWJ79KQW618TCO4NO3DE5XCTJNJLT	A2M3KQ9CKP7YW	Option1|Option3
	2U1RJ85OZIZENUSKFVFO05EW4MKX9V	A2MCI9K0K5VX50	Option1|Option3
	2EB79KQW618NAEC75L44FXCE8CCKMS	A2QLSHXNCHBRN4	Option1|Option3
	2PV95SW6NG1FYB58DS2YP1FZ7OKVHG	A323WW03VM8089	Option1|Option3
	2V7395SW6NG1L0LXOWAB8F1FEHYUGR	A37WXDYYT7RCZ0	Option2|Option3
	2Z4GJ2D21O3WB5ZA9YGSS2KYTFL7DU	A3E8SXH0BAYG85	Option1|Option3
	20WJ3NAB6BFMLN68ORK13JFDV4SGTP	A3G3G7SCD88G1J	Option1|Option3
	291O9Z6KW4ZMG7ZRH0CF00ON2LRE5F	A3O81LHBBI8NPK	Option1|Option3
	22LLB3L0FBJ9OWTT4SIE5E5R4H2XLV	A3RLCGRXA34GC0	Option1
	20SONNVRH1KHUHWQHKY6XV9LZM7OX3	AFB9N61OMZXCX	Option1
	2Z8FL6VCPWZ9XVV68XM127SNI3U8N1	AO3XB5I5QNNUI	Option3
	2FZDZKPFE4EGJPVWSEC8S9NZBWI6G5	AOOJY0XKNYJYZ	Option3

HITId	AssignmentId	WorkerId	Worker Preferences
HIT 7	22O6NG1FS3NYTRT85A6Z2ZL2CHIZLC	A2QQKVIN9R45N6	Option1
	25H3TVOK5UFJB9GHGNFZPYQSG2A74Z	A3QB0Z9AN62HFH	Option1
	27MLRGNTBJ3MSLFF5YYNG2KHQZ4U8W	A323WW03VM8089	Option1|Option2|Option3
	291RNDWIOV1SD05D327UB3YDEY5HWX	A1FQGVP8SX5WE2	Option1|Option2|Option3
	299HRRLFQ0ONT39RRT8OJEGRQXPQH3	A1VKSXDK4QAEF9	Option1|Option2|Option3
	29R2MIKMN9U8VHGDY2NW7I3S9O1RAU	A3O81LHBBI8NPK	Option1
	2BTK274J79KQ2EJIDDXU7FCDJVEFHW	A233ONYNWKDIYF	Option1|Option2|Option3
	2CYDG67D1X3V6N2A2XB2TE1MMF2HAM	A166A2M31CW2C7	Option1
	2I0MQU6L5OBVIQJ1N6VASJF7VKJEX7	A3F6SDO4GYBE4Y	Option1|Option2|Option3
	2JJJ85OZIZEHSISZCXFQFEWPCBEYA1	A22XK2FSFIAAFG	Option1|Option2|Option3
	2KTQP6AUC26DMEPNR6UVAFK0RE592K	A30MLBCTI3OWIR	Option1|Option2|Option3
	2LFFSVGULF39B0EGDPSF23NY29VN9O	A2S96ZZ70YFPSK	Option1|Option2|Option3
	2N52AC9KSSZV35K0UELUUQOYVD11JO	A2QLSHXNCHBRN4	Option1|Option2|Option3
	2Q5HDM25L8I9T7EG7NQ6YE4QBXAQG2	A3RLCGRXA34GC0	Option1
	2R08MQU6L5OB1K0BH6O4KIJFM6BWD2	A37WXDYYT7RCZ0	Option1
	2TCM05BMJTUH44KQJY0RK7S5BCKKF7	A1MHGD46DB5Z7H	Option1|Option2|Option3
	2TTLY58B727M6QYPAQ41GYFSA5OU9N	AYG3MF094634L	Option1
	2U91Q6SVQ8H8EU84WUWOLVCIGHF4N7	A3G00Q5JV2BE5G	Option1|Option2|Option3
	2W2ZHHRRLFQ0UV55HQSKRO9EVHSFOK	A2QD7QFGCUNF5N	Option1|Option2|Option3
	2WBUNU8LZ6R76ON1ZH48T3VEMMA4K2	A646R8SV0S04Y	Option2|Option3
HIT 8	29YR70G5R98DERL54GNS2TNYR63RB6	A13T61GJTR2Y9B	Option1
	2Q5HDM25L8I9T7EG7NQ6YE4QBWSQGI	A198SS8SV0LWKB	Option1
	2I64BLYHVI44U0KUB3ZDXEZSQ0Q1VR	A1FQGVP8SX5WE2	Option2
	2790JPPSI2KYKX32FGWKVM6WYTPJPS	A1MHGD46DB5Z7H	Option1
	209M8JIA0RYNPHKX9TD0FBMJ8JG05C	A22XK2FSFIAAFG	Option2
	2OJILKH1Q6SVWGZIYVHUGL5OQLC0J1	A233ONYNWKDIYF	Option2
	2CXL8I9NZW6HK7OY4DHWHT86O5TLVD	A2FUPODRRCESB	Option3
	2SDKH1Q6SVQ8NGQWG3XLFOBVR7Z2LL	A2HM35CWB7IIFM	Option2
	2R8YQ4J3NAB6HN4P5XPYST1TY5DQDB	A2JH6SJZDJHZ9I	Option3
	2QB2D21O3W5XN81ZF192UYEP0IPF9P	A2M3KQ9CKP7YW	Option2
	254NHMVHVKCJ69JUSGVJH9KQBW235E	A2MCI9K0K5VX50	Option2
	2XEHGYQ4J3NAHETPCO6O8YITGIIOBR	A2QLSHXNCHBRN4	Option2
	2ZO1INMHGYQ4PB5K1F2FWFFODNH7K4	A323WW03VM8089	Option1
	2VSXULRGNTBJ9U4NNE6PHN62Z7BS6A	A37WXDYYT7RCZ0	Option2
	26TINMHGYQ4J9VSLWK6MPFOYD8TL8B	A3E8SXH0BAYG85	Option2
	28L3DHJHP4BDJSYEOHIS79X3VS4W3K	A3G3G7SCD88G1J	Option2
	298KPEIB9BAWR047FZWV7UD31JR0XP	A3O81LHBBI8NPK	Option2
	2UHFE4EGDHDM8D3I8IEZ66HEEWOKAB	A3RLCGRXA34GC0	Option2
	2I988MQU6L5OH3USR0OXEAIJUXGCVR	AO3XB5I5QNNUI	Option2
	25J14IXKO2L98PWMMJXXDYOCR51CBM	AOOJY0XKNYJYZ	Option2

HITId	AssignmentId	WorkerId	Worker Preferences
HIT 9	224M6IAA2SEI02CAQXHKUA4IXIQMMK	A2QQKVIN9R45N6	Option2|Option3
	22CMT6YTWX4H9PKZ1D49JGI6X98W1C	A3RLCGRXA34GC0	Option2
	22FTL0XULRGNZJ1DCV4XFFP72WKP33	A646R8SV0S04Y	Option1|Option2
	25CCJ011K274PFRUG5X1IN469NWAC5	A22XK2FSFIAAFG	Option2
	25GK5UFJ51Y7WM6957HSBCST1EYB8X	A3O81LHBBI8NPK	Option2
	25GK5UFJ51Y7WM6957HSBCST1EZ8BV	A1VKSXDK4QAEF9	Option2
	276RSQV66RLPNQBD74NA5KI6HD1C4X	A166A2M31CW2C7	Option2
	2AJYNJ92NJKM6DTW92LH8W2G8FRC7H	A323WW03VM8089	Option2
	2CI45UUKQOYGTQEBD1ZOQ010MIDEWE	A3F6SDO4GYBE4Y	Option2
	2E1F9SSSHX11PW52JE85P8J43FJVZQ	A233ONYNWKDIYF	Option2
	2F73Q0JG5TYMTKE81D0FJSSSWNKJF7	A2MCI9K0K5VX50	Option1|Option2|Option3
	2GMXFCD45XCEZVV2D2BIX3TG4UIWYB	A37WXDYYT7RCZ0	Option2
	2HIEOZFYQS1CY14Y56ID24ICG4HILZ	A1SFABJ4NX5DFY	Option2
	2N9JHP4BDDKGA6Q1I60XDG35MMSZ63	A1FQGVP8SX5WE2	Option1|Option2
	2QGOGQSCM6IAGAAO83LUA0OQZATHHY	A1MHGD46DB5Z7H	Option1|Option2
	2R7L42J1LY58HFKHC99GPKHDGWGP4O	A3G00Q5JV2BE5G	Option2
	2RN8ER9Y8TNKOUH2CEBFRS2O1Q8T6J	AYG3MF094634L	Option1|Option2
	2VNWJ5OPB0YVM7Q8C527OP9UIRLX5Q	A2QLSHXNCHBRN4	Option1|Option2
	2WBUNU8LZ6R76ON1ZH48T3VEMMAK4I	A2QD7QFGCUNF5N	Option1|Option2|Option3
	2Z8SNTL0XULRMVBL9CDMNX5F4X51NR	A3QB0Z9AN62HFH	Option2
HIT 10	20K1CSTMOFXRJ0MS2A5YNNXJUE1SPK	A2QQKVIN9R45N6	Option3
	23NOK5UFJ51YDYWYPOPQ21CS8EWA77	A1SSBN3C7NEPEO	Option3
	25CCJ011K274PFRUG5X1IN469PXACA	A2QLSHXNCHBRN4	Option3
	2C55NQYN5F3Q6RYFJ7DNMWYBJ1L8CS	A3O81LHBBI8NPK	Option3
	2CBE1M7PKK9LX4OYPJ30ELZX4DGZSK	A1FQGVP8SX5WE2	Option3
	2F3MJTUHYW2GZXR10GJ56M16OQWJOI	A3RLCGRXA34GC0	Option3
	2FTY7QEOZFYQY9U2JVFF7RDSJAUFIU	A3G00Q5JV2BE5G	Option3
	2GGQ1SNQQ7Q6D8NBGT3N112T54C8SR	A1VKSXDK4QAEF9	Option1|Option3
	2JJJ85OZIZEHSISZCXFQFEWPCDCAYF	A166A2M31CW2C7	Option3
	2KNKI62NJQ21DAHJZZ86LKLCA59UM2	A3B3AKQ9G1VX9J	Option1|Option3
	2MOYB49F9SSSN5JB9XES35H5U0PVRQ	AYG3MF094634L	Option1|Option3
	2NRXR24SMEZZ8U0UCW0UIP9YI01I1M	APXNY64HXO08K	Option1|Option3
	2RSJPPSI2KYEVTAZXEBLW6WJIF7KQH	A2QD7QFGCUNF5N	Option1|Option3
	2U4J011K274JDH20MFS8X46UC6ADBM	A2BO8M77CS3SGZ	Option3
	2U91Q6SVQ8H8EU84WUWOLVCIGJ44N0	A1X258MWJFEMTW	Option1|Option3
	2UIW618N46UXLKVEV63E3NDS2LOOQE	A22XK2FSFIAAFG	Option3
	2W2ZHHRRLFQ0UV55HQSKRO9EVIAOFD	ARQ9DY4UL4WJ4	Option1|Option3
	2XIY2RCJK63Z1MLRH9BUSAQ9YD66VY	AM2W23THD4CI7	Option1|Option3
	2Y1Z6KW4ZMAZNP91BOH0YNNV680G7E	A1F4D2PZ7NNWTL	Option1|Option3
	2Z0JVCNHMVHVQK1ARAB2H4J7OCQ20K	A2KJ50DARKEBPR	Option3

Appendix C

Conceptual Similarity Crowdsourcing Evaluation: Experiment 2 Results (Part 1)

This appendix display 10 sample results of human collective opinion experiment conducted on Amazon Mechanical Turk service to evaluate the performance of the proposed conceptual similarity comparison algorithm described in Chapter 5. The HIT assignment used in the experiment is as in Figure 5.9 (page 109). The sample results in this appendix correspond to the following HITs.

HIT NO	Queries	Candidates
1	The Car Doctor	Specialist Cars
2	Landlook	Property Look Pty Ltd
3	Bodytone	Bodytalk
4	Rug Cleaning Experts	carpet-cleaning-specialist.com
5	Computerman	The Computer Guy
6	Gas Master	Gas Experts
7	Star Ballroom	Planet Ballroom
8	Deep Sea	Deep Ocean Planet
9	First Ideas	An Original Idea
10	Gold Line	Lacegold

Table C-1 The HITs queries and candidates used in the Crowdsourcing experiment, which correspond to the results provided in this appendix

HITId	AssignmentId	WorkerId	Worker Score
HIT 1	20AHPCGJ2D21UBEFNQRJZPSIHEIA43	A3G3G7SCD88G1J	2
	211Y8TNKIMZSSD2P71TOW0PGA9JAXE	ALQPGVQZEZSUE	1
	22NGULF395SWCVYB51UN8NJBD9HQCZ	A9K0CV70JWG1W	1
	254NHMVHVKCJ69JUSGVJH9KQB0I352	AIQB7XXL5K2FR	2
	2790JPPSI2KYKX32FGWKVM6WYX9PJQ	AFB9N61OMZXCX	0
	28XCOW0LGRZ3EK9PBLXVXUZWSLHZ8W	A2QD7QFGCUNF5N	1
	291O9Z6KW4ZMG7ZRH0CF00ON2P85EV	A16G716K9428HM	2
	2APULRGNTBJ3SUV7VOG7X62KW5PT7N	A1K9WP8Q74E9G2	1
	2BNP9746OQ1STY8HGFY0F1QKRH7M2Z	A38EHOL0U2BTV0	1
	2BWIXKO2L92HKKEKW6UYYCCFF68DED	A3RLCGRXA34GC0	2
	2CYDG67D1X3V6N2A2XB2TE1MMJ2AHN	A18PC9QU8N3DXS	1
	2ERMAZHHRRLFW86XD4IHBKHOO82DM5	A2QQKVIN9R45N6	0
	2FLYMNCWYB49LHA2IQO1BJON7NOQMK	AYG3MF094634L	1
	2HW6OQ1SNQQ7WEPAVAHKMNR1HN7Q68	AHZK68L2UCA70	0
	2PV95SW6NG1FYB58DS2YP1FZ7T1VH7	AURYD2FH3FUOQ	0
	2QXR98D8J3VED4A2JWPCQ3MCZ2TWGM	A2XFGTPDO4KQ2B	1
	2TAA0RYNJ92NPS4AVKDJ3UHYBW094N	A1F4D2PZ7NNWTL	2
	2TCM05BMJTUH44KQJY0RK7S5BGIFK8	A2BO8M77CS3SGZ	0
	2YM3K4F0OHOVX9MSNTF2V92HT6D127	A2M3KQ9CKP7YW	2
	2ZBWKUDD8XMB9YLJP9264TO68YVCNZ	A1RDT8BS8A8S76	0
HIT 2	23EOFXRDS4IC7MGND6AFW11AHCFXUH	AFB9N61OMZXCX	2
	23QMNCWYB49FF0A276S1TONS8ZXRNJ	A1RDT8BS8A8S76	2
	26B5OPB0YVGZE6461G5PJU31H1EZ7C	AYG3MF094634L	2
	27CO2L92HECWGEFDOX3CP0CPKEEGH4	A3RLCGRXA34GC0	1
	27J24SMEZZ2MOS4XZ3ZPJY388QD3KN	A2GHZI45J9CN9R	1
	280TNKIMZSM5QNZ2SXD0ZGVFIC3CZG	A2BO8M77CS3SGZ	0
	28GCCF0CP5KXV10X8ROYQ4PMMHEVW7	A1K9WP8Q74E9G2	1
	2ADWSBRI8IUB86CJYS8S3LB30UX3FM	AHZK68L2UCA70	1
	2BWIXKO2L92HKKEKW6UYYCCFF65DEA	ALQPGVQZEZSUE	1
	2JM8P9Y38TWW3QL2K79MAJTAVHQIZR	A1F4D2PZ7NNWTL	2
	2MFHMVHVKCJ0792CXDA7JKQWLVP464	A2QD7QFGCUNF5N	1
	2OFLVWJ5OPB043Y9Y7DWL7EPOOKV31	A18PC9QU8N3DXS	0
	2P3NFSVGULF3FDA6WW71PS3NDHYM81	A9K0CV70JWG1W	0
	2R9RRLFQ0ONN1ZZBAQF9OGRBM04RI4	A2M3KQ9CKP7YW	1
	2RX7DZKPFE4EMLZNCBWLII9NEQPF5P	A3G3G7SCD88G1J	2
	2TZ9KQW618N4C2FP2MV57CET279LNO	A16G716K9428HM	0
	2UE05BMJTUHY2AY3FIIAHS5W1VNGLB	AURYD2FH3FUOQ	0
	2UFQY2RCJK6353WD70RK4IAQOD4U53	A2XFGTPDO4KQ2B	0
	2XEHGYQ4J3NAHETPCO6O8YITGNZBO5	A38EHOL0U2BTV0	0
	2XLL0XULRGNTHRLWCMO5PP7NLW0Q4M	AIQB7XXL5K2FR	1

HITId	AssignmentId	WorkerId	Worker Score
HIT 3	21DPHIT3HVWA1S0GSWAQC172E3QKC2	A18PC9QU8N3DXS	1
	223RI8IUB2YUFG1RI2CBDL0FQDP6IK	A2BO8M77CS3SGZ	2
	24VK4F0OHOVR7C07AXTLJ2HERQR230	A1RDT8BS8A8S76	0
	25CI62NJQ21787RJGQXBULCVT5ANV8	ALQPGVQZEZSUE	0
	25OAVKI62NJQ89PCPI0QR6BK06DSK5	AYG3MF094634L	2
	268KCCVLL3CA9B4R0YH4M9NQ91DX7A	A16G716K9428HM	0
	27MYT3DHJHP4HLVU6DP81SX9CXXU1J	AURYD2FH3FUOQ	0
	280E4BLYHVI4AWACAUL8NNEZ75Q0UL	A1K9WP8Q74E9G2	0
	2C5IPDOBDDP8VREUKM487MB35XT1CJ	A1F4D2PZ7NNWTL	2
	2DLVOK5UFJ514F8OE86Y0S1C7N3965	A2M3KQ9CKP7YW	0
	2IBHSTLB3L0FHRRSEKAETREVTZAUID	A3G3G7SCD88G1J	0
	2JZ46OQ1SNQQDYOHQESQUCNRGW9P5Z	A2QD7QFGCUNF5N	1
	2KSRYNJ92NJKS8NLCSKURYW2VN7B6I	AHZK68L2UCA70	0
	2L2T2D5NQYN5LB8A9PWT8MNCBSU59N	A3RLCGRXA34GC0	2
	2P3NFSVGULF3FDA6WW71PS3NDH4M87	AFB9N61OMZXCX	1
	2R8YQ4J3NAB6HN4P5XPYST1TY9ZDQS	A2QQKVIN9R45N6	2
	2SFMHGYQ4J3NGJOL5V6FYYYI8VAANV	AIQB7XXL5K2FR	2
	2SY2NJQ2172ZFH8RWKBLMVEB9VIPX8	A38EHOL0U2BTV0	1
	2TX1Y7QEOZFYW0JMI2DOPXRD7YXHEM	A9K0CV70JWG1W	2
	2Y4CF0CP5KXPZQ5S86PGEPM72SPWXE	A2XFGTPDO4KQ2B	0
HIT 4	20SONNVRH1KHUHWQHKY6XV9LZQQOXU	A2XFGTPDO4KQ2B	2
	2F3MJTUHYW2GZXR10GJ56M16OSAOJ5	AHZK68L2UCA70	1
	2GP3YOCCF0CPBSFZJREISXYGJJ3TSB	AURYD2FH3FUOQ	1
	2H51X3V0FK0CUSKT4AD7ZKK90LDMFK	A2M3KQ9CKP7YW	2
	2IBVCNHMVHVKIRIBRTT7EJ79ZKC13H	A38EHOL0U2BTV0	1
	2IF46UXFCD453KW3DMJN3KININWTVF	A1RDT8BS8A8S76	2
	2MOA6X3YOCCF6K7FA6GTSNIICSYPQE	A3RLCGRXA34GC0	1
	2NMCF806UFBNL0DQKU63J5SWLHZ0E7	AYG3MF094634L	2
	2OWEGDHDM25LEQRXP5XHOZ6OTY7DN0	A16G716K9428HM	2
	2PB51Y7QEOZF4YAB21KMYFXRSMPGDZ	AFB9N61OMZXCX	2
	2RN8ER9Y8TNKOUH2CEBFRS2O1U5T6O	A1K9WP8Q74E9G2	2
	2T6NLVWJ5OPB66DQPHPM6B7E43C2U9	A18PC9QU8N3DXS	0
	2UIW618N46UXLKVEV63E3NDS2N2QOY	AVX3SWFMBEPMZ	2
	2V7395SW6NG1L0LXOWAB8F1FEMFUGI	A2BO8M77CS3SGZ	1
	2VQ58B727M0IMN2R3AXYPSVFJPXBWG	A9K0CV70JWG1W	2
	2WBUNU8LZ6R76ON1ZH48T3VEMQBK4R	A3G3G7SCD88G1J	2
	2WF9U8P9Y38T24FST1LYSM0J84VXGC	ALQPGVQZEZSUE	2
	2WFCWYB49F9SY0Z7RAAOXST5WZZTPY	A1F4D2PZ7NNWTL	2
	2XIY2RCJK63Z1MLRH9BUSAQ9YFLV66	AIQB7XXL5K2FR	1
	2ZNH8MZ9O9Z6Q4M9CJQHRRRLUKG903	A2QD7QFGCUNF5N	2

HITId	AssignmentId	WorkerId	Worker Score
HIT 5	200H88MQU6L5UJDM8AIX74AIY9NUB1	A2BO8M77CS3SGZ	1
	20QN5F3Q0JG5Z64X25PBE9F97MACGS	A3RLCGRXA34GC0	2
	21T4IXKO2L92NMU60FO38OCCUUTCDH	AHZK68L2UCA70	2
	22FTL0XULRGNZJ1DCV4XFFP720LP3C	A2XFGTPDO4KQ2B	1
	24QT3DHJHP4BJL2QU7ZR2X9XIAJV2P	AIQB7XXL5K2FR	2
	25SFK0COK2JE7UPZAT0L1W6OE4SRKE	A1RDT8BS8A8S76	1
	268KCCVLL3CA9B4R0YH4M9NQ91CX79	A9K0CV70JWG1W	2
	2BUA1QP6AUC2CLYGXMSXDV0FZUS07I	ALQPGVQZEZSUE	2
	2GG33FDEY5CO283QH8U8MRFLR0C1SA	A38EHOL0U2BTV0	1
	2IEQU6L5OBVCO997ND1ITF7G9VSYFN	AYG3MF094634L	2
	2JJJ85OZIZEHSISZCXFQFEWPCFCYA7	A2QD7QFGCUNF5N	2
	2KSRYNJ92NJKS8NLCSKURYW2VN96BF	A1F4D2PZ7NNWTL	2
	2M8W40SPW1INSPY8GDA3XAB6Q93E1M	AURYD2FH3FUOQ	2
	2O4WA6X3YOCCL8UZVTOP3INIXRHPO7	A3G3G7SCD88G1J	2
	2S1NZW6HEZ6OKC86X2Z6JGUMHVHPZ6	A16G716K9428HM	2
	2SUKYEPLSP75QT4GMSUOKHQE5P0WQF	A2M3KQ9CKP7YW	1
	2VHHIT3HVWAVQQOCDSH2B72ZO38DLZ	A323WW03VM8089	1
	2YC2JE1M7PKKFT96WXQAM04LER5QX1	A1K9WP8Q74E9G2	2
	2Z8FL6VCPWZ9XVV68XM127SNI7AN84	A18PC9QU8N3DXS	1
	2ZO1INMHGYQ4PB5K1F2FWFFODS0K7A	AM2W23THD4CI7	2
HIT 6	20SJG5TYMNCW4JMJ5IJS2HX1GD3MI9	ALQPGVQZEZSUE	2
	21B85OZIZEHMGI7WEXH5OWPX0R2BZ7	A1RDT8BS8A8S76	1
	226IUUU00OQKQIMS81ZSCU26NUZUUN	A2QQKVIN9R45N6	2
	22C9RJ85OZIZKP4K0YDOYQ5EBJE8WG	A3RLCGRXA34GC0	2
	25OAVKI62NJQ89PCPI0QR6BK06ESK6	A1F4D2PZ7NNWTL	2
	28F5F3Q0JG5T4U5MM724JF9S7MWHDT	A9K0CV70JWG1W	1
	29NXX2Q45UUKWWGQDRN1XS8OVUGSAN	A1K9WP8Q74E9G2	2
	2CTO3W5XH0JPV00CA75PVSP7KE2JD2	A2M3KQ9CKP7YW	2
	2GPBAT2D5NQYTDXDG9AGFTYM26D37H	AIQB7XXL5K2FR	2
	2KTQP6AUC26DMEPNR6UVAFK0RI192O	AURYD2FH3FUOQ	0
	2O41PC6SK9RJED69885HWAAP1I6Q2S	A3G3G7SCD88G1J	2
	2O8DHDM25L8IFVH6WQ5ZGOE45QPFPA	A18PC9QU8N3DXS	2
	2PB51Y7QEOZF4YAB21KMYFXRSMLDGS	A16G716K9428HM	2
	2PVQ0JG5TYMNI4GLUI692SSHCVJGK9	AHZK68L2UCA70	1
	2S2A2SEIUUU06W8UAJVISS8SHOLQQ7	AYG3MF094634L	2
	2TLUHYW2GTP9XIP2V5D1G9YS39NMRE	A2BO8M77CS3SGZ	2
	2TUD21O3W5XH6R7ZIRTK8EPL7JNGAS	A2QD7QFGCUNF5N	2
	2UFQY2RCJK6353WD70RK4IAQOD15UB	A38EHOL0U2BTV0	1
	2VYVCPWZ9RND2Q65R1YSX3DTVOMBQI	AFB9N61OMZXCX	2
	2YUGMMEGOOGQYK4G8J122EIU9OJBB4	A2XFGTPDO4KQ2B	1

HITId	AssignmentId	WorkerId	Worker Score
HIT 7	20KCM6IAA2SEO2C4Q9FQUKA4XCCLLP	A1F4D2PZ7NNWTL	2
	20Q2RCJK63ZVKBZ1QTLIKQ9J0Z77WR	ALQPGVQZEZSUE	2
	2626X3YOCCF0IXNUNYKIXIIXDALRQ7	A2M3KQ9CKP7YW	1
	26W0SPW1INMHM68E9CEAL6BF191G32	AMUC6OI4A2GY4	1
	273AT2D5NQYNBNL0QS753YMNRQI48T	AFB9N61OMZXCX	1
	28349F9SSSHX791YD1K5R5F8YY4XTM	AURYD2FH3FUOQ	0
	2AGHOVR14IXKUA3JSQ5C6A6XIS587E	A16G716K9428HM	1
	2C2C9KSSZVXX8YMFK3BQYYGNXQI3LQ	A3RLCGRXA34GC0	1
	2IBVCNHMVHVKIRIBRTT7EJ79ZKF13K	A2XFGTPDO4KQ2B	1
	2NU1O3W5XH0JVXASSTPEZLSPMZ1ICP	A2BO8M77CS3SGZ	1
	2PI0ONNVRH1KNWRO6027GNV90EFWNU	AYG3MF094634L	1
	2PKVGULF395S2E5QROJ3XYNJQSVPB0	A1RDT8BS8A8S76	0
	2UE05BMJTUHY2AY3FIIAHS5W1VOGLC	AHZK68L2UCA70	0
	2USCOK2JE1M7VS2JB0N6YZACFY1NUJ	A9K0CV70JWG1W	1
	2VHHIT3HVWAVQQOCDSH2B72ZO36DLX	A1K9WP8Q74E9G2	2
	2VQ58B727M0IMN2R3AXYPSVFJPZBWI	A18PC9QU8N3DXS	1
	2VR6R70G5R98JG1DLNYW2STND6YQAZ	A3G3G7SCD88G1J	2
	2W2ZHHRRLFQ0UV55HQSKRO9EVLSOF1	AIQB7XXL5K2FR	2
	2WL6YTWX4H3H8XTE3I0GS6IJ65KY3B	A38EHOL0U2BTV0	0
	2XBKM05BMJTUN6EC62G91A7SKQ2JEU	A2QD7QFGCUNF5N	2
HIT 8	22KZVXX2Q45U0S8YOPEI61NSNIXQ8U	AHZK68L2UCA70	1
	23UD5NQYN5F3W81QV2PMXCWYQYQ7BC	A1RDT8BS8A8S76	1
	2626X3YOCCF0IXNUNYKIXIIXDALQR6	AIQB7XXL5K2FR	1
	26NOX7H57DZKVNWE4P4HNM2502Z0AA	A16G716K9428HM	1
	27EB3Q39Z0B6016GJD5V2TVRZA8VKE	A1F4D2PZ7NNWTL	2
	28XCOW0LGRZ3EK9PBLXVXUZWSLIZ8X	AURYD2FH3FUOQ	0
	29R2MIKMN9U8VHGDY2NW7I3S9S1ARL	AYG3MF094634L	2
	2CFJQ2172Z99WPOLAU3VOBU1ID4RZZ	ALQPGVQZEZSUE	1
	2E1F9SSSHX11PW52JE85P8J43JMVZ1	AFB9N61OMZXCX	1
	2IQ1THV8ER9YE15U8VQSW5KFWMJ2PC	A2BO8M77CS3SGZ	2
	2IQ1THV8ER9YE15U8VQSW5KFWMM2PF	A3G3G7SCD88G1J	1
	2IS6UFBNFSVG0TXDZEJWGNG1UMOI4G	A2QQKVIN9R45N6	2
	2K5ZXR24SMEZ5A4SAVE948P9DXR0HN	A2XFGTPDO4KQ2B	2
	2KRHHRRLFQ0OTVD17ABHY9EG65OPGI	A18PC9QU8N3DXS	0
	2MOA6X3YOCCF6K7FA6GTSNIICSWQPD	A1K9WP8Q74E9G2	1
	2O41PC6SK9RJED69885HWAAP1I3Q2P	A2QD7QFGCUNF5N	2
	2OKCWY2AOO2GSUWQEX7Q2CM6X4Q33B	A38EHOL0U2BTV0	1
	2RQW2GTP9RA7YDEWRF0Y2OF7FD1UPL	A9K0CV70JWG1W	2
	2S20RYNJ92NJQUIF1VAT4HYWHABA56	A2M3KQ9CKP7YW	1
	2Z7E4EGDHDM2BTQSZWQWGHEZLIWBLQ	A3RLCGRXA34GC0	1

HITId	AssignmentId	WorkerId	Worker Score
HIT 9	21Q0LWSBRI8I0JK8KIZJRSTLQX4D1U	A3RLCGRXA34GC0	1
	240LZ6R70G5RFGVI9CMEHWSS8HF8O4	AIQB7XXL5K2FR	2
	26UGTP9RA7S52UJGZ7JOP70J1B3RWC	AYG3MF094634L	1
	280E4BLYHVI4AWACAUL8NNEZ75S0UN	AHZK68L2UCA70	1
	2AT1K274J79KW4OBYWV64XFCSYLEGL	A1RDT8BS8A8S76	0
	2BTK274J79KQ2EJIDDXU7FCDJZEHF6	A18PC9QU8N3DXS	1
	2GYRLPHIT3HV2IDU8FTNTQ21MWFIAM	ALQPGVQZEZSUE	1
	2KYX3YOCCF0CVD27F29NSIXYVY9SR0	AFB9N61OMZXCX	2
	2LDYHVI44OS2QTCI3W5Z2BAPK5M4Y8	A1F4D2PZ7NNWTL	2
	2LEJTUHYW2GTVH9KX1WWW169DM9KPK	A2QQKVIN9R45N6	2
	2MHWZ9RNDWIO19AHIWUD3GU1ISXTED	AMUC6OI4A2GY4	0
	2OFLVWJ5OPB043Y9Y7DWL7EPOOI3V7	A9K0CV70JWG1W	1
	2PD6VCPWZ9RNJ40YLAJ72N3D8AAPA5	A2QD7QFGCUNF5N	2
	2SL3HVWAVKI68V10SAY2999QW0UGOU	A2XFGTPDO4KQ2B	1
	2SPKO2L92HEC2IO7T7FCMF0C4Z1FG5	A2BO8M77CS3SGZ	2
	2TEJUNU8LZ6RD8YFHIZDIJ3VT1F3JQ	A3G3G7SCD88G1J	1
	2V7Q0ONNVRH1QP6J4PIBH6NVOF0VMG	AURYD2FH3FUOQ	0
	2V7Q0ONNVRH1QP6J4PIBH6NVOF1MV8	A2M3KQ9CKP7YW	2
	2XKSCXKNQY2RIR2GT8MEDHR0ZOY0PP	A1K9WP8Q74E9G2	2
	2Z0PJWKUDD8XSJL0TIQ0L6UT30AALT	A16G716K9428HM	1
HIT 10	20N66RLPHIT3N3EKLT96CNJQHVR8GK	A3G3G7SCD88G1J	1
	21JLFQ0ONNVRN92REI5G1B762PRKTM	A3RLCGRXA34GC0	1
	23YS8SV7WGKCI33VTL13DMHA4KP0QL	AFB9N61OMZXCX	0
	26UGTP9RA7S52UJGZ7JOP70J1B2WRG	AURYD2FH3FUOQ	1
	26UGTP9RA7S52UJGZ7JOP70J1B4WRI	A2XFGTPDO4KQ2B	1
	2C21QP6AUC26JOOH3AO350FKF6681I	A18PC9QU8N3DXS	1
	2CZ4J79KQW61EVMGK66CN45XR8AKI4	AVX3SWFMBEPMZ	1
	2I6BDPGFL6VCV4HJHW4WSOV17194JA	A1RDT8BS8A8S76	1
	2JCQW618N46U3NUNUEOCOTND7HANPO	A2BO8M77CS3SGZ	1
	2L5DP8PJWKUDJGFW1CH3JZ0BLO9I7V	A9K0CV70JWG1W	1
	2N58XMB3Q39Z6JO4JXXTEEVS8P7SHZ	A16G716K9428HM	0
	2N58XMB3Q39Z6JO4JXXTEEVS8PASH2	A1F4D2PZ7NNWTL	2
	2N9JHP4BDDKGA6Q1I60XDG35MQRZ6A	A2QD7QFGCUNF5N	1
	2PSOHOVR14IXQWKVZB8EMWA6CXG67R	AHZK68L2UCA70	0
	2QHGSNTL0XULXO531SUMWDX5UJN0MT	A1K9WP8Q74E9G2	1
	2SMB2YU98JHSZTTDB96BT9IOQDUBNQ	A38EHOL0U2BTV0	1
	2T12NJKM05BMP1CRO5TG3P9RP1BGBQ	AYG3MF094634L	1
	2T9STLB3L0FBPH0Y1S5J1EVEKL4JVZ	ALQPGVQZEZSUE	0
	2THPSI2KYEPLYXPFAUD66J3OPB6SM8	AIQB7XXL5K2FR	1
	2X9MVHVKCJ017SKHUSY9UQW6G2575C	A2M3KQ9CKP7YW	1

Appendix D

Conceptual Similarity Crowdsourcing Evaluation: Experiment 2 Results (Part 2)

This appendix display 10 sample results of human collective opinion experiment conducted on Amazon Mechanical Turk service to evaluate the performance of the proposed conceptual similarity comparison algorithm described in Chapter 5. The HIT assignment used in the experiment is as in Figure 5.9 (page 109). The sample results in this appendix correspond to the following HITs.

HIT NO	Queries	Candidates
1	The Car Doctor	The Tap Doctor
2	Landlook	Landmark
3	Bodytone	Body Zone
4	Rug Cleaning Experts	Rgs Cleaning Ltd
5	Computerman	Computerland
6	Gas Master	Gas Matters
7	Star Ballroom	Star room
8	Deep Sea	Deep Cee
9	First Ideas	Light Ideas
10	Gold Line	Goldwins

Table D-1 The HITs queries and candidates used in the Crowdsourcing experiment, which correspond to the results provided in this appendix

HITId	AssignmentId	WorkerId	Worker Score
HIT 1	206OZFYQS1CSZU6PN04SEIC1TQIJM4	A3RLCGRXA34GC0	1
	20Q2RCJK63ZVKBZ1QTLIKQ9J0YSW7Z	A1012N48J0Z65N	0
	23D0XULRGNTBPB4W36WFZ7N6HCT5RZ	A2XFGTPDO4KQ2B	0
	24IIHPCGJ2D27WL6V680TPPSXU8932	A166A2M31CW2C7	1
	24S0OQKKA4IIYGACKBX8AEW0RSFZZO	A2QD7QFGCUNF5N	1
	25OJ5OPB0YVG5GGWMKYEZ9U3GUM6YL	A2HM35CWB7IIFM	1
	280E4BLYHVI4AWACAUL8NNEZ74S0UL	A34M93NJC830DP	0
	2DI39Z0B6UTOC1MOL1KV1KGPBK2NY3	A22XK2FSFIAAFG	1
	2FD8I9NZW6HE5E6OUZN73869VNZWMM	A3J2CI4J5V3MLP	0
	2GKVQ8H88MQUCTNY143IBRXXJ3SR8N	A3AJLUNBK4EU68	0
	2I0MQU6L5OBVIQJ1N6VASJF7VM8EX0	A2NX62E91H15U8	0
	2N58XMB3Q39Z6JO4JXXTEEVS8NASHY	AURYD2FH3FUOQ	0
	2NRXR24SMEZZ8U0UCW0UIP9YI021I6	AWRAXV1RIYR0M	0
	2NU1O3W5XH0JVXASSTPEZLSPMXQCI4	AYG3MF094634L	0
	2R9RRLFQ0ONN1ZZBAQF9OGRBMY0IRN	A1E6RS45GUAFC3	0
	2RGVR14IXKO2RHKR4LNAGX3Y34VA9U	ABM77ZQWCHPNX	0
	2TCM05BMJTUH44KQJY0RK7S5BFVFKJ	A2F0NZQ8F9ON8C	0
	2THPSI2KYEPLYXPFAUD66J3OP9WSMU	A3O81LHBBI8NPK	0
	2V7395SW6NG1L0LXOWAB8F1FELSGUF	A3UY8NHC9OBOIT	2
	2VR6R70G5R98JG1DLNYW2STND40AQH	A2QLSHXNCHBRN4	0
HIT 2	20QN5F3Q0JG5Z64X25PBE9F97K5CGJ	A2XFGTPDO4KQ2B	1
	21DFQ0ONNVRH7SZYZN7RL76NA2MLUY	A1012N48J0Z65N	1
	23EOFXRDS4IC7MGND6AFW11AHA1XUZ	A22XK2FSFIAAFG	1
	23VDHJHP4BDDQOM8Y0JXJX3GIXQ4XW	ABM77ZQWCHPNX	1
	254NHMVHVKCJ69JUSGVJH9KQBY935P	AWRAXV1RIYR0M	1
	26W0SPW1INMHM68E9CEAL6BF17ZG3W	AURYD2FH3FUOQ	0
	2DVFDEY5COW0RO99TH3RPLC6AF03U5	A3RLCGRXA34GC0	2
	2E3LYHVI44OS8S34YMEE9SBA4XR3X7	A2HM35CWB7IIFM	1
	2EYOQ1SNQQ7QCFIFRZBCXR128IW7RO	A2QLSHXNCHBRN4	0
	2IEZ9O9Z6KW45US97QIRVFQ03FUC35	A2NX62E91H15U8	0
	2KRHHRRLFQ0OTVD17ABHY9EG63CGPT	AYG3MF094634L	2
	2KSRYNJ92NJKS8NLCSKURYW2VL2B69	A1E6RS45GUAFC3	0
	2MGK2JE1M7PKQH31MFFZKC040RIPWH	A166A2M31CW2C7	0
	2PD42J1LY58BDAPWQR7FUHD1LQNQ5F	A2QD7QFGCUNF5N	2
	2QMLF395SW6NM9X2TWPNTBYFG7IES4	A2LFVJ28A2J2PK	2
	2VJGNTBJ3MMD3DXZXWX2UHB9167AWD	A3AJLUNBK4EU68	1
	2YC2JE1M7PKKFT96WXQAM04LEQ2XQ3	A3J2CI4J5V3MLP	1
	2YM3K4F0OHOVX9MSNTF2V92HT5Q21J	A2F0NZQ8F9ON8C	1
	2Z46SK9RJ85O5QHO7V1AZMOO5YW5TK	A34M93NJC830DP	0
	2Z8SNTL0XULRMVBL9CDMNX5F4ZTN15	A3O81LHBBI8NPK	1

HITId	AssignmentId	WorkerId	Worker Score
HIT 3	21Z0G5R98D8J93WHM1JTXYCGIFTDTZ	A34M93NJC830DP	0
	2BC274J79KQWC9QXUFLXPCD4KPTIGV	A2HM35CWB7IIFM	1
	2CCYEPLSP75KRUO69CFARQEQABZRXR	AWRAXV1RIYR0M	1
	2CWE6AUBXHWSNFXVZIMB9WDR0PP2Y5	A2QLSHXNCHBRN4	1
	2CZ4J79KQW61EVMGK66CN45XR6YIKM	A3RLCGRXA34GC0	2
	2E6GDHDM25L8OH59MF8E96OEJI2EOU	AYG3MF094634L	1
	2ERMAZHHRRLFW86XD4IHBKHOO63DM2	A166A2M31CW2C7	0
	2I988MQU6L5OH3USR0OXEAIJU0ACVR	A3UY8NHC9OBOIT	1
	2JJNDWIOV1S7YVLNJPL1DYDZNFQXI3	ABM77ZQWCHPNX	1
	2M7806UFBNFS1OCV5C052W6NVTN2GV	A2QD7QFGCUNF5N	1
	2R8YQ4J3NAB6HN4P5XPYST1TY7QQDS	A1E6RS45GUAFC3	0
	2RGVR14IXKO2RHKR4LNAGX3Y34I9AG	A3O81LHBBI8NPK	1
	2RX7DZKPFE4EMLZNCBWLII9NEOQ5FC	AURYD2FH3FUOQ	0
	2SMUU00OQKKAAQ02Y1TUC680TPCWWC	A3J2CI4J5V3MLP	2
	2TAA0RYNJ92NPS4AVKDJ3UHYBVO949	A3AJLUNBK4EU68	1
	2TLUHYW2GTP9XIP2V5D1G9YS38SMRH	AO3XB5I5QNNUI	1
	2X4WYB49F9SSYPFBRSFN2T5HK7JUQ4	A2XFGTPDO4KQ2B	1
	2XBKM05BMJTUN6EC62G91A7SKOSEJB	A22XK2FSFIAAFG	1
	2YV3FDEY5COW6TY1PCZC1FLCLOOT2Q	A1012N48J0Z65N	1
	2ZV6XBAT2D5NW65F5CH0TG5TDET51X	A2NX62E91H15U8	1
HIT 4	20Q2RCJK63ZVKBZ1QTLIKQ9J0X7W7C	A2HM35CWB7IIFM	1
	21U4SMEZZ2MIQU5JKHG9838TBO64L0	AWRAXV1RIYR0M	2
	224M6IAA2SEI02CAQXHKUA4IXKPMMN	ABM77ZQWCHPNX	1
	22IV66RLPHIT9PD604BIG2NJ5VV7F5	A3UY8NHC9OBOIT	2
	254NHMVHVKCJ69JUSGVJH9KQBYL533	AURYD2FH3FUOQ	0
	26QB49F9SSSH39JTEWJTFH5FNB9WSO	AYG3MF094634L	2
	28IS1CSTMOFXXLAE8LSE8DNXY8FRO9	A2F0NZQ8F9ON8C	2
	2CYDG67D1X3V6N2A2XB2TE1MMHQHAE	A3RLCGRXA34GC0	2
	2GJ70G5R98D8PBDOX5JS3NYCVVSCSW	A3O81LHBBI8NPK	1
	2H51X3V0FK0CUSKT4AD7ZKK90J3MF6	A2QD7QFGCUNF5N	1
	2J0D8J3VE7WSY1582PUMMK8A8U6ZJ7	A2XFGTPDO4KQ2B	2
	2NHGFL6VCPWZFZ5NMRFVBS7S2WUM7E	A34M93NJC830DP	2
	2NTX3V0FK0COQA1ORVYPUK9L6OPNGI	A2QLSHXNCHBRN4	1
	2PV95SW6NG1FYB58DS2YP1FZ7RWVHY	A1E6RS45GUAFC3	0
	2QLP9RA7S5WM7ER8IX67AJMH03UTYI	A3J2CI4J5V3MLP	1
	2TVNAB6BFMFFU6GSJAKJPDGE759IVE	A3AJLUNBK4EU68	1
	2WL6YTWX4H3H8XTE3I0GS6IJ645Y3U	A1012N48J0Z65N	2
	2X5WIOV1S7SN9LBQKAUYNZ8NNJ0ZK0	A22XK2FSFIAAFG	1
	2X5WIOV1S7SN9LBQKAUYNZ8NNJEZKE	A166A2M31CW2C7	0
	2Z1746OQ1SNQWF8GX9W10KCN6T84OE	A2NX62E91H15U8	0

HITId	AssignmentId	WorkerId	Worker Score
HIT 5	20N66RLPHIT3N3EKLT96CNJQHU8G87	A1012N48J0Z65N	2
	21Z0G5R98D8J93WHM1JTXYCGIEHDTL	A2NX62E91H15U8	1
	23MHYW2GTP9RGFAFMVS6JYSOU0DNSY	A3J2CI4J5V3MLP	2
	2BANMHGYQ4J3TITG1ODFPOYYXLE9M7	A1E6RS45GUAFC3	1
	2BPERSQV66RLVP03TQMWKVKILVT3BQ	A3AJLUNBK4EU68	2
	2FTY7QEOZFYQY9U2JVFF7RDSJAVFIV	A2QLSHXNCHBRN4	0
	2J0D8J3VE7WSY1582PUMMK8A8U1JZM	A3O81LHBBI8NPK	0
	2K36BFMFFOYYO1J39O4GOSC06P8YLI	A2XFGTPDO4KQ2B	2
	2KYX3YOCCF0CVD27F29NSIXYVWXRSJ	AWRAXV1RIYR0M	1
	2M1KSSZVXX2QADC4AZFYQNIWGFA5NH	ABM77ZQWCHPNX	1
	2MGK2JE1M7PKQH31MFFZKC040R3PW2	AYG3MF094634L	1
	2RE8JIA0RYNJFA5TAVR5LMJT99I61S	AURYD2FH3FUOQ	0
	2RHCGJ2D21O32DFRQSGP2I2KD7IC6Z	A3UY8NHC9OBOIT	2
	2S0IUB2YU98JN0BV1CC0PBJ9XHSL9N	A34M93NJC830DP	1
	2TVNAB6BFMFFU6GSJAKJPDGE748VIO	A2QD7QFGCUNF5N	1
	2UHFE4EGDHDM8D3I8IEZ66HEEYUKAL	A3RLCGRXA34GC0	2
	2XM8LZ6R70G5XHQNYSUVO7WS7L57NY	A2HM35CWB7IIFM	1
	2Y1Z6KW4ZMAZNP91BOH0YNNV69M7GT	A166A2M31CW2C7	1
	2YC5UFJ51Y7QKWHPOZJ1MSTM3739CI	A22XK2FSFIAAFG	1
	2YM3K4F0OHOVX9MSNTF2V92HT5P12H	A2F0NZQ8F9ON8C	2
HIT 6	23UD5NQYN5F3W81QV2PMXCWYQXNB7B	A3J2CI4J5V3MLP	2
	25CI62NJQ21787RJGQXBULCVT30VN2	AYG3MF094634L	0
	25ZWGKCCVLL3IILDCQ1P04C92I0V5C	A2MCI9K0K5VX50	1
	27VV0FK0COK2PMJWXYBKJLRWLG5IPO	A2NX62E91H15U8	0
	28M98JHSTLB3R8XL9I9OLJEJ661FRM	A22XK2FSFIAAFG	1
	298KPEIB9BAWR047FZWV7UD31L00X2	A2QD7QFGCUNF5N	1
	29PR24SMEZZ2SQ2WDIL8Z9Y3NL82J3	A1E6RS45GUAFC3	1
	2BNP9746OQ1STY8HGFY0F1QKRFWM2K	A3RLCGRXA34GC0	2
	2C521O3W5XH0PX728BBYOPLS4ZDBH5	AWRAXV1RIYR0M	0
	2CWE6AUBXHWSNFXVZIMB9WDR0PO2Y4	AURYD2FH3FUOQ	0
	2ERMAZHHRRLFW86XD4IHBKHOO6LMDT	A3O81LHBBI8NPK	1
	2PKVGULF395S2E5QROJ3XYNJQRVPBY	A166A2M31CW2C7	1
	2PQQS1CSTMOF3ZV2UR31OYDNCB8QNQ	A1RDT8BS8A8S76	0
	2QXTYMNCWYB4FNR2I18XB1JO2LULP2	A1012N48J0Z65N	2
	2RHCGJ2D21O32DFRQSGP2I2KD7V6C6	A3AJLUNBK4EU68	1
	2S9PCGJ2D21O94N779APZSI2ZQQB5S	A2XFGTPDO4KQ2B	2
	2VHHIT3HVWAVQQOCDSH2B72ZO18DLV	ABM77ZQWCHPNX	2
	2VYVCPWZ9RND2Q65R1YSX3DTVMKBQC	A2QLSHXNCHBRN4	1
	2Z8SNTL0XULRMVBL9CDMNX5F4ZX1NN	A38QM2WVQ7O9MF	2
	2ZO1INMHGYQ4PB5K1F2FWFFODQYK74	A2HM35CWB7IIFM	1

HITId	AssignmentId	WorkerId	Worker Score
HIT 7	20W5UUKQOYGNO4JXIHFGA1077NBXFP	A2VE5IV9OD2SK1	2
	22FQQ7Q67051WSUXHATT0C1X18OCWB	A3RLCGRXA34GC0	2
	22IV66RLPHIT9PD604BIG2NJ5UA7FI	AWRAXV1RIYR0M	2
	23MHYW2GTP9RGFAFMVS6JYSOU09NSU	A3AJLUNBK4EU68	1
	240LZ6R70G5RFGVI9CMEHWSS8GAO8D	A3J2CI4J5V3MLP	1
	247J51Y7QEOZL682RLJTWOFX650FCI	A2QD7QFGCUNF5N	2
	28F5F3Q0JG5T4U5MM724JF9S7KTDHI	A2XFGTPDO4KQ2B	1
	28TTHV8ER9Y8ZV2SC8JMFKFH7UUQ3N	A3O81LHBBI8NPK	1
	28XPQJQ9OPLL3KP4C0OGIKCOEED1ZE	A34M93NJC830DP	2
	2JUNJKM05BMJZ2Z8MB7TZ9RAMKCCHC	A2NX62E91H15U8	2
	2N58XMB3Q39Z6JO4JXXTEEVS8NAHSN	AURYD2FH3FUOQ	1
	2N58XMB3Q39Z6JO4JXXTEEVS8NDSH1	A166A2M31CW2C7	1
	2TLUHYW2GTP9XIP2V5D1G9YS37JRMB	A1E6RS45GUAFC3	1
	2TNCNHMVHVKCP8JBABY4T79K5OP42L	A2QLSHXNCHBRN4	1
	2UA62NJQ21725HR07F2KVCVEQM6OWJ	AYG3MF094634L	1
	2W2ZHHRRLFQ0UV55HQSKRO9EVJROFW	A2HM35CWB7IIFM	1
	2W6ZZ2MIKMN90G7JOCZT6WXIILV8P3	A1012N48J0Z65N	1
	2XXF3Q0JG5TYSVU6OKV9P9SS792IE2	A22XK2FSFIAAFG	1
	2ZBWKUDD8XMB9YLJP9264TO68WVCNV	ABM77ZQWCHPNX	1
	2ZNH8MZ9O9Z6Q4M9CJQHRRRLUJT90E	A2F0NZQ8F9ON8C	1
HIT 8	21ALKH1Q6SVQEPQICZL6V5OBA4Z1KP	ABM77ZQWCHPNX	0
	24MU00OQKKA4OQAIIBL2G80EBTKXXV	A3AJLUNBK4EU68	1
	262VKI62NJQ27FK9ZIHHGBKLROFLT7	A1012N48J0Z65N	0
	291RNDWIOV1SD05D327UB3YDE0THWP	A3O81LHBBI8NPK	0
	2DC4F0OHOVR1AQFUEBC9CHECB2J43Q	A2XFGTPDO4KQ2B	0
	2FFQYN5F3Q0JMDB8CW3W8B49U1XAEQ	A22XK2FSFIAAFG	0
	2GYRLPHIT3HV2IDU8FTNTQ21MU4AIZ	A3RLCGRXA34GC0	2
	2HOGKCCVLL3CGBLW7JGQEC9N5MJ6WJ	A1E6RS45GUAFC3	0
	2IDZ6R70G5R9ELQTT4576SST2QI9PW	A2MCI9K0K5VX50	0
	2IS6UFBNFSVG0TXDZEJWGNG1UKA4IK	APXNY64HXO08K	0
	2JZ46OQ1SNQQDYOHQESQUCNRGU95PB	A2HM35CWB7IIFM	0
	2O4WA6X3YOCCL8UZVTOP3INIXP5OPQ	A2QD7QFGCUNF5N	2
	2OAUUU00OQKKGC0SIHJ24268F79VVS	A3J2CI4J5V3MLP	0
	2PKVGULF395S2E5QROJ3XYNJQQMBP9	AYG3MF094634L	0
	2PSOHOVR14IXQWKVZB8EMWA6CWC67L	A166A2M31CW2C7	1
	2S0IUB2YU98JN0BV1CC0PBJ9XGU9LB	AURYD2FH3FUOQ	0
	2SSOUQIHPCGJ8LKBECN57H0J4HY065	A2NX62E91H15U8	0
	2UET6YTWX4H3NA7LUM09QI6IYKRX2S	A34M93NJC830DP	0
	2X4WYB49F9SSYPFBRSFN2T5HK7FUQ0	AWRAXV1RIYR0M	1
	2YP7H57DZKPFKCWQ3Q4MC5L8X16C26	A2QLSHXNCHBRN4	1

HITId	AssignmentId	WorkerId	Worker Score
HIT 9	22EEZZ2MIKMNF2QZZ7U83WWXXVYO7I	A2NX62E91H15U8	0
	22O1VP9746OQ7050GGH6H0515D5K0J	A2F0NZQ8F9ON8C	0
	2626X3YOCCF0IXNUNYKIXIIXD9XRQH	A3UY8NHC9OBOIT	2
	26R9RNDWIOV1YFAXTMKG413YSSLVG3	A3J2CI4J5V3MLP	0
	26WZMAZHHRRLLYIYDWMRR1KH31JLCQ	A22XK2FSFIAAFG	1
	273AT2D5NQYNBNL0QS753YMNROI84T	AURYD2FH3FUOQ	0
	28URCJK63ZVE9P9AA39A09JLKJA8XV	A3O81LHBBI8NPK	0
	2C5IPDOBDDP8VREUKM487MB35VR1CD	ABM77ZQWCHPNX	0
	2GGQ1SNQQ7Q6D8NBGT3N112T5498SO	AWRAXV1RIYR0M	1
	2GYRLPHIT3HV2IDU8FTNTQ21MVEIAJ	A166A2M31CW2C7	1
	2HW6OQ1SNQQ7WEPAVAHKMNR1HLYQ6V	A1E6RS45GUAFC3	0
	2IKV7WGKCCVLRBUKTCDHKPQ4R1W3TH	A2QD7QFGCUNF5N	0
	2LFVP3TVOK5ULRNBOGHEYZFY5K752E	AYG3MF094634L	1
	2QKNTL0XULRGT1TTTVDD75FPMFIO28	A2XFGTPDO4KQ2B	1
	2S0IUB2YU98JN0BV1CC0PBJ9XGSL9L	A2HM35CWB7IIFM	1
	2THPSI2KYEPLYXPFAUD66J3OPAYMSS	A3AJLUNBK4EU68	1
	2TX1Y7QEOZFYW0JMI2DOPXRD7WOHE9	A3RLCGRXA34GC0	1
	2UA62NJQ21725HR07F2KVCVEQNHOWW	A34M93NJC830DP	0
	2UG2L92HECWAC5L8EL3FACP5ZQPHIE	A1012N48J0Z65N	0
	2YC2JE1M7PKKFT96WXQAM04LEP8QX0	A2QLSHXNCHBRN4	0
HIT 10	2C521O3W5XH0PX728BBYOPLS587BHI	A1F4D2PZ7NNWTL	1
	2LUYU98JHSTLHB3A5KA9SOBJUK6DP9	A1K9WP8Q74E9G2	0
	2SDKH1Q6SVQ8NGQWG3XLFOBVSJA2LL	A1RDT8BS8A8S76	0
	2NHGFL6VCPWZFZ5NMRFVBS7S34F7M1	A1X258MWJFEMTW	1
	2DJY0LWSBRI8O2TCO308THST1C8C0R	A22XK2FSFIAAFG	1
	2BWIXKO2L92HKKEKW6UYYCCFGDREDC	A2QD7QFGCUNF5N	0
	2DGU3K4F0OHO1ZJE86BOCL92XFR100	A2QLSHXNCHBRN4	0
	2PQQS1CSTMOF3ZV2UR31OYDNDKGNQE	A2QQKVIN9R45N6	0
	2YI1SNQQ7Q676DJ0ALERB2TQS2YT9Z	A31XT6RPLN6359	0
	2RHCGJ2D21O32DFRQSGP2I2KEFR6CJ	A323WW03VM8089	0
	2PC0COK2JE1MDX2UZUIWGOZAS16MTS	A38EHOL0U2BTV0	0
	2Z46SK9RJ85O5QHO7V1AZMOO66AT53	A3AJLUNBK4EU68	0
	2I3727M0IGFKNLJGOOJVP4VI4V2EZC	A3O81LHBBI8NPK	0
	2NTX3V0FK0COQA1ORVYPUK9L7XKGNP	A3RLCGRXA34GC0	1
	2OGZFYQS1CSTSWX7HMJ4SC1EEEONKM	A9K0CV70JWG1W	0
	2ZYAUC26DG67J9FDL96KACOKIKK5C6	AFB9N61OMZXCX	0
	2K5ZXR24SMEZ5A4SAVE948P9E4AH02	ALQPGVQZEZSUE	0
	2IBIA0RYNJ92TR2WQE2MTTUHEX4384	ARQ9DY4UL4WJ4	1
	2EXUUKQOYGNI2952YX70B07SBHCGY3	AURYD2FH3FUOQ	0
	2QMLF395SW6NM9X2TWPNTBYFHG1SEK	AYG3MF094634L	0

Appendix E

Degree of Similarity Aggregation Evaluation

This appendix display 10 sample results of human collective opinion experiment conducted on Amazon Mechanical Turk service to evaluate the performance of the proposed aggregation method described in Chapter 7. The HIT assignment used in the experiment is as in Figure 7.9 (page 145). The sample results in this appendix correspond to the following HITs.

HIT NO	Queries	Option 1	Option 2	Option 3
1	webautor	WEBIATOR	autoscout24	WebFOCUS
2	NEXT	Nexans	NEST	NR
3	SKYPINE	SKY ROOM	SKYLINE	DECOLINE
4	RIMOSTIL	Rivotril	REFODERM	REBOVIR
5	Lifestyle	Living Style	LIFE TEX	SNOW LIFE
6	WOOD STONE	MOONSTONE	WILTON	SwissTron
7	NUTELLA	NATURE ELLA	NATURESSA	MARQUELA
8	bonvita	BONAVITA	Botoceutical	biovital
9	FMH	FTG	MR	FNH
10	ACTIVIA	ACTEVA	ADWISTA	ACCET

Table E-1 The HITs queries and candidates used in the Crowdsourcing experiment, which correspond to the results provided in this appendix

HIT No.	AssignmentId	WorkerId	Option 1 Score	Option 2 Score	Option 3 Score
HIT 1	32EYX73OY09U7UGB8DEBPT7243EURJ	A6U5ZHN5Y953Q	3	1	2
	3483FV8BEEJS1Z9PX5178FLEPPG26A	A2KFBIPESKBKWK	4	1	4
	34J10VATJFYPM26B1H0X109MEMOIQX	A2ZUKYMM3YV6JN	3	1	2
	358UUM7WRZ3S9J4FV5L0F1TIWSF7RS	A20ALQT1HIVSAH	4	1	3
	37QW5D2ZRGM8AC9BKZDBJBU9TE58S5	A2OLVF6P86QSQJ	4	1	3
	3907X2AHF050B5RUC10GEFCVKU6P23	A207IHY6GERCFO	4	1	2
	39ZSFO5CA8WD96XY0852N2LBUMKUJR	A9LSEP71DNP4O	3	1	3
	3A1PQ49WVHH193BAAKSX0N0Z6XI1HT	A2B8HPIZDKYKDR	2	1	3
	3FTYUGLFSULJL57RPBBJCSYIQLTD5D	A39QOA9M7GNF86	3	1	1
	3HHRAGRYX85TQP0SIA2GZ2FJGVJO9C	A1QK90OHMNVT6N	5	1	1
	3JRJSWSMQHLLZWYN7NYA3DIJC143E7	A3MSTD6XFKI1GK	3	1	2
	3K5TEWLKGVBHRA2SNGU77N8UVE3IVR	A35NBUVLJDU499	4	1	2
	3L4PIM1GQTGBO30GIEB0SEDF0ROYRK	A3N0S7OYDTXU1S	3	1	1
	3NS0A6KXC48K4317YPJ77H8A4CHZGG	A2XFO0X6RCS98M	2	1	2
	3RYC5T2D73THFP8FRRFHFNK3WMMRPK	A1LRJ2MQD4AMES	3	1	3
	3T3IWE1XG6NFVGMMVTZ1F7BVP34QTM	A1PJLZSOUQ4MIL	4	1	2
	3VELCLL3GKJHV7K4FU4XX2OMQI5F19	AGTV2SNFKXB11	3	1	2
	3WMINLGALB36MJDUKB7P0XWMXZJCAJ	A1835XBNR2UB4X	4	1	3
	3WOKGM4L71GBUVCFIEJN6REQDRPO00	A166A2M31CW2C7	3	1	3
	3ZPBJO59KP1V1YRMQDCS1P18VULHDZ	A142ZRU284W9O	4	1	3
HIT 2	31LVTDXBL7ARO4THZZMAY6BJRCKLRF	A1UUNYHX3M8O3O	3	4	1
	323Q6SJS8IGSZI5IHJ7IPP4T770FH7	A2OLVF6P86QSQJ	3	4	1
	34QN5IT0TZR893PZBXUR95OQYMN08B	A2KFBIPESKBKWK	4	5	2
	37XITHEISW9YL0ZBMMTBVNLWX36RC5	A9LSEP71DNP4O	3	4	1
	3B1NLC6UGZWQQZZ1BGL5GJ6WUDBPGM	A9QYAH5BONH1W	3	4	1
	3D8YOU6S9EK1LBIRGPBDEYG68G06UX	A2ZUKYMM3YV6JN	3	4	1
	3EJPLAJKEMGI7AC1MCALVQVLAYF6ZM	A1PJLZSOUQ4MIL	2	4	1
	3FIJLY1B6U4KCZ360WFNYY6KTYAFPC	A20ALQT1HIVSAH	3	4	1
	3LEIZ60CDJZ5PTEZKJDXF0MN0ZMZ9P	A38898UQ3SLHES	3	4	2
	3MB8LZR5BFT510GM9FDDXUP5WKQLKM	A14PFRHG0A2YY9	3	4	1
	3N1FSUEFL501PM3RB6S970S4QPZ4D0	A2B8HPIZDKYKDR	3	5	1
	3N2BF7Y2VQUY5SXZ36BVKFO248DMHM	A1835XBNR2UB4X	2	4	1
	3NG53N1RLVJBXKTJSI9HO6PY6UY8PP	AGTV2SNFKXB11	2	3	1
	3NLZY2D53PPRC3EHMKXATG1EVQILQE	A1LRJ2MQD4AMES	2	4	1
	3PS7W85Z8Z293H50EROFTCL6F30T93	A2IBLAKBXPA6PQ	2	2	1
	3RRCEFRB7MC8AP57XA13CA44N4N4BT	A166A2M31CW2C7	2	2	1
	3S06PH7KSR4KXN68OO9792L1E5PD1W	A207IHY6GERCFO	3	4	1
	3TMSXRD2X60J6T6Z5JEX1QAMLLV1WT	A142ZRU284W9O	4	5	1
	3TVSS0C0E10KFDI872Y77WTHD4LWTW	A3N0S7OYDTXU1S	2	5	1
	3XUHV3NRVKY0XLCTB7U93DDGIDO5HG	A35NBUVLJDU499	4	5	1

HIT No.	AssignmentId	WorkerId	Option 1 Score	Option 2 Score	Option 3 Score
HIT 3	30X31N5D63QMT02QHXXPF204J25SAT	A2KFBIPESKBKWK	4	5	2
	3180JW2OT4CWOR7JZ7XUFQTVV5S5JL	A39QOA9M7GNF86	1	4	1
	33NF62TLXJ2Z6ASM6U10HFCDSVMJKJ	A14PFRHG0A2YY9	3	5	2
	33OOO72IVHLB1FC3QBY6V2MELO3TCK	A2OLVF6P86QSQJ	4	5	2
	34T446B1C0EAL6FCS9AWBRK9OD7C0S	A9LSEP71DNP4O	3	4	2
	34YB12FSQYOK5W2OJ0TDZFC1P80MGN	A207IHY6GERCFO	2	5	1
	35GMH2SV3EHALLR9QLI2RGGU7SZOEM	A1835XBNR2UB4X	3	4	1
	38SKSKU7R1XEV5QY9CS1KEAS4G1IL8	AGTV2SNFKXB11	2	3	1
	3B837J3LDOWESHO7J8JBASPEJ6TRS0	A1PJLZSOUQ4MIL	1	4	1
	3CP1TO84PT1WIV9BSMR2G97ETU525U	A26T6O5EFR54A9	4	5	1
	3JZQSN0I3QAEZMA7XDP04PSSS7NFG8	A2B8HPIZDKYKDR	4	5	2
	3LOTDFNYA7ZAW807CITIQSEGMVDWFO	A1LRJ2MQD4AMES	3	4	2
	3NS0A6KXC48K4317YPJ77H8A4CIGZY	A20ALQT1HIVSAH	4	5	2
	3PDJHANYK5GWGPC7GQ4EVJRGE8YH67	A2ZUKYMM3YV6JN	1	3	2
	3S0TNUHWKTI28NQTN9IMOC89SBVD8G	A3EG4C9T4F5DUR	2	4	2
	3TPZPLC3M0CPWNNDG1ELXPHNQ86P3E	A3N0S7OYDTXU1S	1	2	1
	3VJ40NV2QINCA496GG7XQ2GVA2MTOH	A142ZRU284W9O	3	4	2
	3X65QVEQI0NNI24YH2WF9BCXRBICL1	A2XFO0X6RCS98M	3	4	3
	3YZ8UPK3VTMQ1SRSQGOG0Y8G42BUCD	A35NBUVLJDU499	3	5	1
	3ZWFC4W1UU75OCJLDOJC3T6ZUGZFR5	ALML8V38FDV0	2	4	1
HIT 4	31Q0U3WYDPF4GE5YXB6L9AB5SUM71X	A207IHY6GERCFO	4	1	2
	32AT8R96GL9689GON2EGF3CYQ5WSU4	A20ALQT1HIVSAH	3	1	2
	32SCWG5HIH4OT6AVZ3CJ4ST70Z86P1	A9LSEP71DNP4O	4	2	3
	37WLF8U1WPQNIFDFMB7B8B786P2K6E	A2XFO0X6RCS98M	3	2	2
	38JBBYETQOA6HSHR713TDIAPQ10E43	A2B8HPIZDKYKDR	5	1	2
	39K0FND3AHFJV5PLX0133T1YRDMAMY	A35NBUVLJDU499	5	3	4
	3A0EX8ZRN8OO8WJRMHPASZ8BI5LYB7	A2OLVF6P86QSQJ	5	2	3
	3AQF3RZ558IC2TL1L0GESYF3YTL6FY	A1MU86MFDSXPBH	3	1	2
	3DY4FPOOA1OUK95BD3OGLF9LIAMVR8	A1UUNYHX3M8O3O	4	1	3
	3GLB5JMZFXVH12WB67UAGPP7GU7DGV	A1835XBNR2UB4X	4	2	2
	3IKZ72A5B4GK9ERTKH2VU91PTJ9FNG	AGTV2SNFKXB11	4	3	1
	3IKZ72A5B4GK9ERTKH2VU91PTJAFNH	A1PJLZSOUQ4MIL	5	2	2
	3LOZAJ85YDD5KETLYSAX8SYYMTG2X5	A2ZUKYMM3YV6JN	2	1	2
	3OHYZ19UGC57V8AXAGGGVXQ3MD1AOD	A142ZRU284W9O	5	2	3
	3ON104KXQKW0YS3IS1XZZOHPX54W40	A14PFRHG0A2YY9	4	1	2
	3TXMY6UCAEOY9ZKB974BQXBR1H5CQQ	A39QOA9M7GNF86	4	1	1
	3V26SBZTBDEKVKWCOH7WSOOGF2CZZ6	A9QYAH5BONH1W	4	2	3
	3WYP994K17RI2K2WQQ82HJMJ44AY6M	A3N0S7OYDTXU1S	4	2	2
	3Z4AIRP3C6DYVTBPFOAJ39OTUN11XM	A1LRJ2MQD4AMES	3	1	2
	3Z4GS9HPNVAIR0K0MRNUAK2IVGM77U	A26T6O5EFR54A9	4	2	3

HIT No.	AssignmentId	WorkerId	Option 1 Score	Option 2 Score	Option 3 Score
HIT 5	33JKGHPFYCUQFOJA6468PZLYQKMMNV	A2B8HPIZDKYKDR	4	2	1
	37TD41K0AH9AMFZO1BTGLXQSJ5QCSF	AGTV2SNFKXB11	4	2	1
	39GAF6DQWR06R46UF991FOR8ECT1VJ	A1PJLZSOUQ4MIL	3	2	1
	3AAJC4I4FGSUV5R86V4A4U0QW4YZJK	A166A2M31CW2C7	4	1	1
	3C2NJ6JBKAH08KFHWMNOAQ70KF62NL	A1LRJ2MQD4AMES	4	2	1
	3E337GFOL98QNENOV18DCU11UYAGNH	A3MSTD6XFKI1GK	4	2	2
	3KXIR214I4GEMC5BEH8SBH10TYA42R	A2XFO0X6RCS98M	4	3	2
	3MTMREQS4VIF0HJZ127QCR3PPF0WAB	A207IHY6GERCFO	5	2	1
	3NAPMVF0ZWFB5ZNUGF6ZETLAK00279	A9LSEP71DNP4O	5	3	3
	3NPI0JQDAO5UV4L7VGKCF2LLK7ITPY	A1835XBNR2UB4X	5	4	2
	3OB0CAO74HPYZ9MDM9Z6EAB9DIRHY7	A2KFBIPESKBKWK	5	4	2
	3PJUZCGDJ6GQ5XDCBTDK2GPJ1QH89V	A14PFRHG0A2YY9	4	2	1
	3QY7M81QH7M6MFRK5LC3EP7410MK7D	A3N0S7OYDTXU1S	4	1	1
	3R2PKQ87NW8Y1N8J9OTGKRPH4LSMIF	A1QK90OHMNVT6N	5	3	1
	3R6BYFZZP7CPL85XMNP4SBSNVXKXFJ	A6U5ZHN5Y953Q	4	2	2
	3SB4CE2TJVVUPHOPB73CEAHWYH8AXK	A2ZUKYMM3YV6JN	4	3	2
	3TVRFO09GKFBL0FT8YS2NOX7ST6LXC	A142ZRU284W9O	5	1	2
	3VAR3R6G1P1TCKHIDIW2Z6K8WP28O8	A20ALQT1HIVSAH	3	2	1
	3WQ3B2KGE8GRIQ8OASI1ECX1BKD1BD	A2OLVF6P86QSQJ	5	4	2
	3WR9XG3T63BL8D2HKTPN78I84EW477	A35NBUVLJDU499	4	2	1
HIT 6	30JNVC0OR9KPQ7VRVZIC1O87E9AHQ4	A166A2M31CW2C7	2	1	1
	30OG32W0SUBS30RXP6IPCRGPHIUNE6	A3MSTD6XFKI1GK	3	2	1
	33C7UALJVLY8GSAH7GYRNA703ES18E	A35NBUVLJDU499	3	2	1
	34S6N1K2ZVJEZAFE3UAGK29D43MLHI	A9QYAH5BONH1W	4	2	1
	35BLDD71I6X3M0R2NKIT7IBKRR6ZV6	A1QK90OHMNVT6N	4	1	1
	3634BBTX0OUSVDG2N1P3P1587KFFI0	A20ALQT1HIVSAH	5	1	1
	37UQDCYH6XVK2QLW4PQAGYILHYS7VL	A3N0S7OYDTXU1S	3	1	1
	39LNWE0K4UWHEVDSIQK2B16BH7UIU2	A2OLVF6P86QSQJ	3	2	1
	39PAAFCODM070OI3HSTBLUA36VJVTL	AGTV2SNFKXB11	4	2	1
	3EKVH9QMEY4RM8O47S9LELV66B2D2C	A111JI6APXR6QV	5	2	4
	3FTOP5WARFOXTKLI21RIYVX4EXH0JV	A207IHY6GERCFO	3	1	1
	3JNQLM5FT4MAKKCWK979XY3BFK4L20	A1MU86MFDSXPBH	4	2	3
	3LBXNTKX0RVGKYEKJ1PCIF6CSZPX9R	A3EG4C9T4F5DUR	4	1	2
	3P1L2B7AD1PORR1177564B6EGP0LO6	A1LRJ2MQD4AMES	3	1	1
	3QRYMNZ7FYHUSJ9UF17KBDGQKSHNTW	A9LSEP71DNP4O	3	2	1
	3S3AMIZX3U54KQG64LYRQY4SI2GCDL	A1PJLZSOUQ4MIL	3	3	2
	3STRJBFXOWRTKDORIOF4JLZMQXCTKX	A142ZRU284W9O	5	2	1
	3TXWC2NHNZQ8OHSLPRJPJ7PKDKNS9E	A2XFO0X6RCS98M	3	1	1
	3VD82FOHKQOVON7VUUC71SGRMGMCOH	A2IBLAKBXPA6PQ	4	3	2
	3ZR9AIQJUB97Q22XZU4EST8LW0Q407	A1835XBNR2UB4X	4	2	2

HIT No.	AssignmentId	WorkerId	Option 1 Score	Option 2 Score	Option 3 Score
HIT 7	32RIADZISS47RBM98WNY2ZE4RS9S4I	A6U5ZHN5Y953Q	1	3	1
	358UUM7WRZ3S9J4FV5L0F1TIWSFR7C	A35NBUVLJDU499	4	5	1
	38JBBYETQOA6HSHR713TDIAPQ104ET	A1IXKR4EJL9CB5	2	5	1
	39O5D9O87TS62YE9BWSFDPIGRPR3CE	A2ZUKYMM3YV6JN	2	4	1
	39O5D9O87TS62YE9BWSFDPIGRPRC3N	A111JI6APXR6QV	2	3	1
	3CCZ6YKWR7J7IFUADV6HQWFSZ0F95T	A1835XBNR2UB4X	2	4	1
	3F6HPJW4JD0QVEOVONEB69KRDRA2WC	A2XFO0X6RCS98M	2	3	1
	3GGAI1SQEVY7OKMJHEXU9ORMRG8MCD	A1LRJ2MQD4AMES	3	4	1
	3IFS6Q0HJIJ1ZILOTLP2W0ONWA9ISM	A2B8HPIZDKYKDR	2	4	3
	3JNQLM5FT4MAKKCWK979XY3BFK62LJ	A142ZRU284W9O	2	3	1
	3L0KT67Y8EGNPI0TX3B5IOIBMT7SY2	A20ALQT1HIVSAH	2	3	1
	3N1FSUEFL501PM3RB6S970S4QPYD48	A9LSEP71DNP4O	3	4	2
	3NGMS9VZTLI8LMECMTJIM4SGRSOFFA	A1PJLZSOUQ4MIL	2	3	1
	3O7L7BFSHEP0PZG6SQ5X7JK8VJ1EII	A3N0S7OYDTXU1S	2	4	2
	3P59JYT76LKY3XK1TI90JPDS9XS2TM	A166A2M31CW2C7	2	3	2
	3TPZPLC3M0CPWNNDG1ELXPHNQ863PS	A2OLVF6P86QSQJ	4	5	2
	3TXWC2NHNZQ8OHSLPRJPJ7PKDKN9SV	A207IHY6GERCFO	2	3	2
	3X4JMASXCM9RB1N6E9E107ER6S7B0K	A14PFRHG0A2YY9	1	3	1
	3XIQGXAUMC8C6FQR44RS4JF6X91X7F	A1UUNYHX3M8O3O	3	4	1
	3Y5140Z9DXG4MQ5W14L81VJC9Q2IP6	AGTV2SNFKXB11	1	3	2
HIT 8	32Z9ZLUT1LKM5VIBGMQ8CJD7Z8SHOW	A1QK90OHMNVT6N	5	2	4
	336YQZE83VEMPZD424AMVILCZZM5MO	A20ALQT1HIVSAH	5	1	2
	33FBRBDW6OZS3VKFNDNB46QR7BJC8F	A35NBUVLJDU499	5	1	2
	386PBUZZXFXAQGA4RUD1WFPSHVRJLM	A166A2M31CW2C7	5	1	2
	38F71OA9GTWERW6T8GNVHUCPOTZFMG	A2B8HPIZDKYKDR	5	1	2
	3GM6G9ZBKNXOA1OU30SKYYRQF28MTW	A2XFO0X6RCS98M	4	2	2
	3GS6S824SQXMK0DOA6CVYXNPOMZNWM	A9LSEP71DNP4O	4	2	2
	3IJXV6UZ1XJPY3LBEWPX6QJRA8RRI8	A1UUNYHX3M8O3O	5	1	3
	3KKG4CDWKIYPMWQAZQN7L49EZ4K94O	A142ZRU284W9O	5	1	4
	3LOZAJ85YDD5KETLYSAX8SYYMTFX2Z	A2ZUKYMM3YV6JN	5	3	4
	3LQ8PUHQFLSC9978IRD3SMHLNZSIH1	A2OLVF6P86QSQJ	5	1	3
	3OS4RQUCR9FI852WHRXM3E1VCUWFBS	A1PJLZSOUQ4MIL	5	1	3
	3PMBY0YE273SH03PS5TP42L2RH19C1	A3N0S7OYDTXU1S	5	1	1
	3RWE2M8QWHATCAC3HZJAR2ELNHM0NZ	A3EG4C9T4F5DUR	5	1	3
	3TAYZSBPLL8XOX7M4I4A9KH67EE2SX	A1LRJ2MQD4AMES	5	2	1
	3X4JMASXCM9RB1N6E9E107ER6S8B0L	AU5Y7J1PF0UIT	5	1	3
	3XLBSAQ9Z4C1BAQ65MFD14VH59YZ7D	A1835XBNR2UB4X	5	3	3
	3YW4XOSQKQL6EPHUAJZWJ2PP05JU1M	AGTV2SNFKXB11	5	1	3
	3Z2R0DQ0JHEWEE243NK5K3DR6N42EV	A207IHY6GERCFO	5	2	3
	3ZQIG0FLQEGZS5MXCXYM8EH2AP1WVC	A2KFBIPESKBKWK	5	3	3

HIT No.	AssignmentId	WorkerId	Option 1 Score	Option 2 Score	Option 3 Score
HIT 9	30H4UDGLT2IQI9VNMJJ0TOQTQZNPMU	A1IXKR4EJL9CB5	4	1	5
	38YMOXR4MUZEDF7WBPQEWM13TWAW6L	A9LSEP71DNP4O	2	2	4
	39K0FND3AHFJV5PLX0133T1YRDNMAB	A142ZRU284W9O	4	3	5
	3B3WTRP3DB2FJIBNVC4JSPCGFQO29L	A2XFO0X6RCS98M	3	1	4
	3BGYGHDBBXK4JYQOA3P4I2429KE22T	A35NBUVLJDU499	4	1	5
	3COPXFW7XBCVSLVK176KEBYP1USPKP	A166A2M31CW2C7	2	1	3
	3EICBYG644WHNCGYEHK2TWZ5NMDCJZ	AGTV2SNFKXB11	2	1	5
	3F0BG9B9MPN16KG190DUNXMFZFUY7L	A2OLVF6P86QSQJ	4	2	5
	3F1567XTNW5WB1D8XNUKO7AJVW29Q6	A2KFBIPESKBKWK	3	1	5
	3FE7TXL1LINLBHS9CEF5EK25PQT2Q8	A1PJLZSOUQ4MIL	3	3	5
	3GA6AFUKOOOXJ6PPXO6GOGFW4HW3HN	A3N0S7OYDTXU1S	2	1	4
	3HMIGG0U4L656YLKJ5501XIAAZ18YJ	A2ZUKYMM3YV6JN	2	1	4
	3HVVDCPGTESO4ID8M3GVSTEXOCLYTX	A1835XBNR2UB4X	3	2	4
	3J4Q2Z4UTY37NXQGQY4C2RIUTXMWQI	A1LRJ2MQD4AMES	2	1	4
	3LEP4MGT3G0LALO0QL2WFEYA0HGDBF	A6U5ZHN5Y953Q	2	1	4
	3URFVVM165I39L22IU8OBW91DKXZUH	A9QYAH5BONH1W	3	2	4
	3V5Q80FXIXRT4GM7E3391C9UFYE234	A207IHY6GERCFO	2	1	5
	3WQ3B2KGE8GRIQ8OASI1ECX1BKEB1O	A3EG4C9T4F5DUR	2	1	4
	3WSELTNVR32N80F56X2FP7WQLLITAI	A2B8HPIZDKYKDR	2	1	5
	3Z7ISHFUH0V5BOVPFR7JF4RCGT58ZA	A20ALQT1HIVSAH	4	1	4
HIT 10	33F859I566D2M1T2CHLM6ZD8S99HBS	A142ZRU284W9O	4	2	1
	35K3O9HUABDGF8EGRIZC4M7GFR9FES	A2XFO0X6RCS98M	4	1	1
	35L9RVQFCOIHI028C82HBP5WHUGUHM	A1LRJ2MQD4AMES	3	2	2
	37WLF8U1WPQNIFDFMB7B8B786P26K0	A9LSEP71DNP4O	5	2	1
	37XITHEISW9YL0ZBMMTBVNLWX37CRR	A2B8HPIZDKYKDR	5	2	1
	37ZHEEHM6WM0QHJDKFK4X3Q2QE073P	A1UUNYHX3M8O3O	2	3	5
	39ASUFLU6X7XFU51RC5YAT7NJW5XE1	A3HZ1AJGUOU1VO	5	2	1
	3AZHRG4CU4KM86JTZGZVIOGFI0V03J	A207IHY6GERCFO	1	1	1
	3C8HJ7UOP7UKWDXT9SH2KMS70YTMZB	A14PFRHG0A2YY9	5	1	3
	3DI28L7YXAEPPTK8KJKRFK3MEHQ1ED	AGTV2SNFKXB11	5	2	1
	3HYA4D452RJOKS20YY4B2LYRIOJF2Q	A1835XBNR2UB4X	5	3	1
	3I33IC7ZWF2TO1LSNIIJOKN0L85A27	A20ALQT1HIVSAH	4	1	1
	3MH9DQ757WC3I47XS2KZQPTV2U3GU9	A1MU86MFDSXPBH	5	1	3
	3P529IW9KYLULEO884MGHHX0OO9LFK	A35NBUVLJDU499	5	3	1
	3QFUFYSY9YFYN6HN2CNZV0VP22FF4M	A26T6O5EFR54A9	4	2	1
	3SB4CE2TJVVUPHOPB73CEAHWYH7XA6	A2ZUKYMM3YV6JN	4	2	2
	3SEPORI8WNZJUCO4CPRXBVX76H4ZA4	A166A2M31CW2C7	5	2	2
	3VAR3R6G1P1TCKHIDIW2Z6K8WP1O8N	A1PJLZSOUQ4MIL	5	3	2
	3X3OR7WPZZ0L6ZEL0QGA7PGE1KX8LR	A2OLVF6P86QSQJ	5	2	1
	3ZSY5X72NXBZUPWECR22QNFDMHQOR0	A3N0S7OYDTXU1S	4	3	2

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