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Procedia Computer Science 60 (2015) 1707 – 1714

Procedia Computer Science

19th International Conference on Knowledge Based and Intelligent Information and Engineering Systems

Feature Extraction Method for Clock Drawing Test

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Abstract

Recently, the number of elderly persons with dementia has been increasing. In the past, we proposed a dementia evaluation system using daily conversations and developed the system with a conversational robot. However, the current system is not ready for practical use because it can only evaluate time/geographical orientation and short-term memory, and some methods to evaluate other orientations and functions is required as well. In this paper, we discuss a new dementia evaluation system using not only daily conversations but also drawing tests. The authors employed a Clock Drawing Test (CDT) as a new dementia evaluation test and implemented it in a tablet device. This paper discusses a feature extraction and recognition method to distinguish normal cases from dementia cases. After evaluation experiments, the proposed method could recognize 87.6% of the clock drawing images.

Peer-review under responsibility of KES International
Keywords: Dementia Evaluation System; Clock Drawing Test; Feature Extraction Method

1. Introduction

Recently, the number of elderly persons with dementia has been increasing, and this trend will become one of the biggest social (and medical) problems in Japan. Fig. 1 shows the dementia population who need living support[1]. This indicates that preventing and alleviating dementia is important. To solve the problem, many studies on robot-assisted therapies have been reported[2]. For instance, Kanoh *et al.*[2] developed a robot-assisted therapy system using a conversation robot. In the system, a conversation robot "ifbot" (Fig. 2), which was retailed by ifoo Inc.[3], was employed for dementia evaluation using simple conversations and quizzes. By using this system, the authors tried to prevent the patient's progression of dementia.

Currently, many welfare facilities employ various tests to evaluate the progression of a patient's dementia symptoms. However, some elderly persons are often nervous about the tests, and consequently the tests cannot be conducted acculately. Generally, these tests should be conducted without their awareness of being tested. To solve the

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Peer-review under responsibility of KES International
doi:10.1016/j.procs.2015.08.280

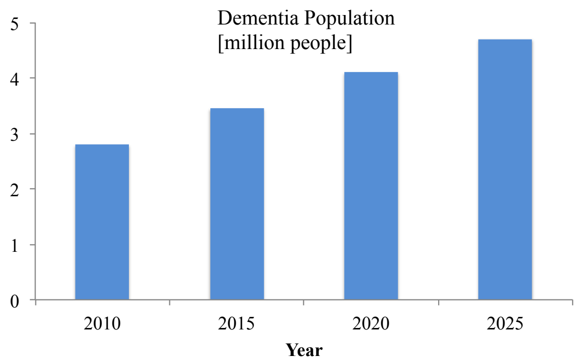

Fig. 1. Dementia population in Japan.

Fig. 2. Conversation robot “ifbot”.

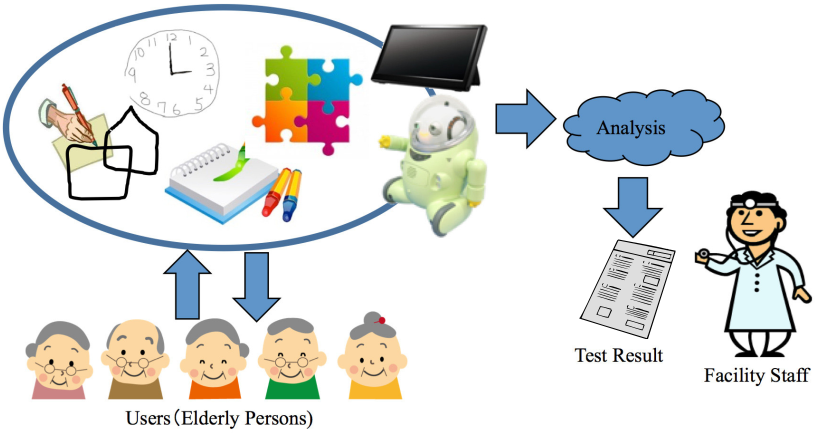

Fig. 3. Summary of our purpose

problem, the authors proposed dementia evaluation methods using daily conversations[4,5,6]. Izutsu *et al.* proposed a conversational content recognition method using a concept dictionary[4]. They employed Japanese WordNet as a concept dictionary and proposed the method to estimate the elderly person’s conversational topics by using conceptional structures of words. In the literature[5], a dementia evaluation method using daily conversations was proposed and evaluation experiments were conducted in welfare facilities. Nagasaka *et al.* proposed the method to control conversational topics for dementia evaluation with daily conversations[6]. These systems, however, are not sufficient for practical use because they can evaluate time/geographical orientation and short-term memory only. Other orientations and functions are also required for accurate dementia evaluation. Therefore, we proposed a new dementia evaluation system using drawing tests as well as daily conversations[8], and we employed drawing tests: a Clock Drawing Test and a Graphic Drawing Test (Fig. 3).

This paper discusses a feature extraction method for a clock drawing test to classify whether the patient has dementia or not. In the proposed method, we employ a Weighted Direction Index Histogram method to extract features from the drawing images, and a Modified Bayesian Discriminant Function is used for discrimination[13,14,15]. By using them, Kajiwara *et al.* could recognize 98.5% of schema images properly[7]. It is expected that the method have capability to recognize clock images accurately. This paper also evaluates the performance of the proposed method in terms of its accuracy and concludes by suggesting future avenues of study.

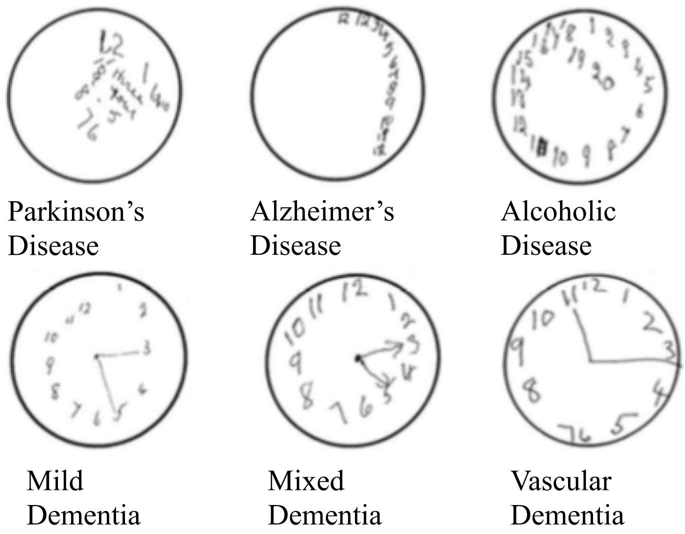

Fig. 4. Examples of dementia images.

2. Materials

2.1. Clock Drawing Test

The Drawing Test is the tests to evaluate a patient's progression of dementia. Some types of drawing tests are often employed for dementia evaluation in welfare facilities. In the drawing test, facility staff give writing materials to an elderly person, who is then instructed to draw a graphic image, usually of a clock. Facility staff or medical personnel then examine the drawing and evaluate the elderly subject's progression of dementia based on the shapes or positions of the clock face and hands. However, these drawing tests can sometimes make the elderly person nervous. To overcome this problem, the tests should be conducted without the subject's awareness of being tested.

Fig. 4 shows examples of clock images drawn by patients. As you can see, features of the images are heavily influenced by disease progression or types. Therefore, many studies on Clock Drawing Test have been reported[9,10,11]. For example, Mohamed *et al.* proposed the feature selection method based on Feature Interaction Maximization (FIM)[9]. In the literature, the authors showed how the method could select features with the higher discriminative power that lead to a deeper understanding of the clock drawing test. Moreover, they presented a novel cascade classifier for diagnosing dementia by classifying clock images. The number of drawings was relatively high compared similar studies[10]. Randall *et al.* proposed a Digital Clock Drawing Test using a digital pen to open up the possibility of detecting subtle cognitive impairment even when test results appear superficially normal. In this article, the authors also developed a training program for technicians who administered the test and classify strokes[11].

2.2. Employed Drawing Images

Generally, a sufficient number of drawing images are required for analysis. Thus we developed a CDT system for tablet devices to collect clock images (Fig. 5). In the experiment, we asked the patients first to draw a clock that indicates 2:55pm. Then patients drew a clock image using an example image. The collected images were used as experimental materials. For control images, a clock drawing test using the developed system was conducted by students at Mie University. We collected 110 clock images which served as our healthy sample. In addition, 100 clock images were given by Cardiff University as dementia images. The details of the image set are as follows.

Table 1. Summary of dementia images.

Disease Type	# of Images
Vascular Dementia (VaD)	37
Mild Cognitive Impairment (MCI)	8
Alzheimer's Disease (AD)	55

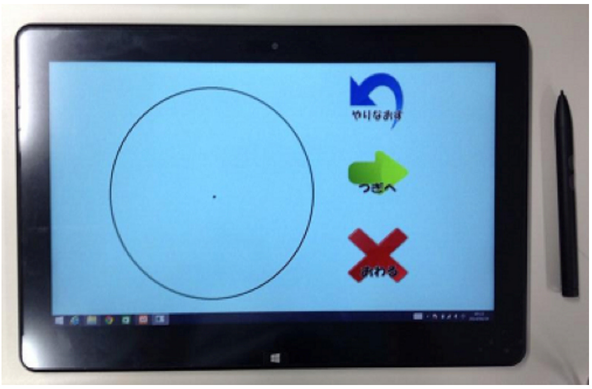

Fig. 5. Clock Drawing Test system using tablet PC.

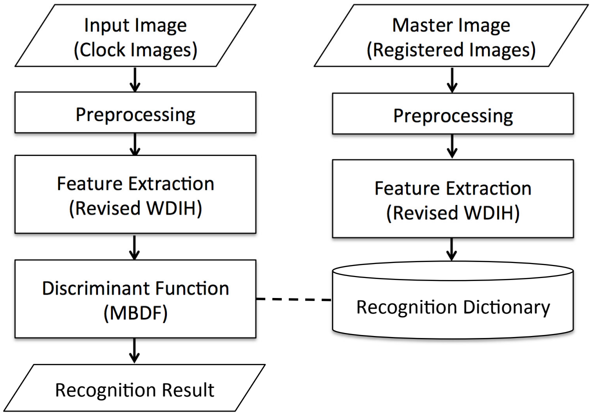

Fig. 6. Flowchart of Recognition Method

3. Methods

The objective of this study is to classify whether a person has dementia or not. Fig. 6 shows the flow of the proposed method. The schema of the proposed method is quite similar to those of other pattern recognition methods. In the first step, binarization, noise reduction and normalization are applied to the images as preprocessing. After this, features are extracted from the input image and the recognition dictionary is generated by using the features. Our method uses Weighted Direction Index Histogram [13,14,15] and Modified Bayesian Discriminant Function [13,14] for feature extraction and discrimination, respectively.

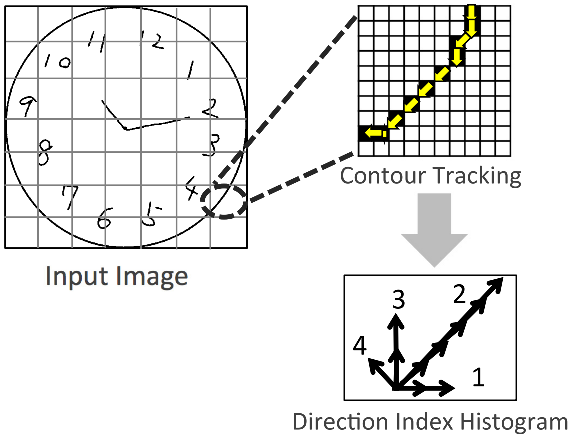

Fig. 7. Applying of WDIH

3.1. Weighted Direction Index Histogram

Weighted Direction Index Histogram (WDIH) is a kind of feature extraction method employed in commercial OCR engines. Fig. 7 illustrates a rough image of the WDIH method. In the method, the input image is first divided into a 7×7 grid of sub-regions. In the next step, the contour of the image is traced, and then the direction index histogram in each sub-region is generated with chain codes. The obtained histogram reflects contour shapes of the clock image in each sub-region. Next, the spatial weighted filter based on Gaussian distribution is applied to the histograms for reduction of dimension. This paper determined the parameters of the filter based on the literature [14]. By this process, the sub-regions are converted to 16 (4×4) sub-regions. Finally, a feature vector is generated by using the values of the histograms about the converted sub-regions.

3.2. Modified Bayesian Discriminant Function

For discrimination function, we employ the Modified Bayesian Discriminant Function (MBDF). The definition of MBDF is given by

$$g(x) = \sum_{i=1}^{k} \frac{\{{}_l\varphi_i{}^T (x - {}_l\mu)\}^2}{{}_l\lambda_i} + \sum_{i=k+1}^{n} \frac{\{{}_l\varphi_i{}^T (x - {}_l\mu)\}^2}{{}_l\lambda_{k+1}} + \ln\left(\prod_{i=1}^{k} {}_l\lambda_i \cdot \prod_{i=k+1}^{n} {}_l\lambda_{k+1}\right) \quad (1)$$

where x denotes the n-dimensional feature vector of the input image, and ${}_l\mu$ does the average vector of clock images l in the dictionary. ${}_l\lambda_i$ and ${}_l\varphi_i$ are the i-th eigen value and eigen vector of the clock image l, respectively. k is determined by the number of learning sample $m(1 \leq k \leq m, n)$. MBDF gives a dissimilarity between the input image and an original clock image in the dictionary. This proposed method outputs a category (AD, VaD, MCI or Normal) with the smallest dissimilarity as a recognition result. The parameters of the discriminant function were initially decided by the literature [13,14].

4. Experimental Results and Discussion

In this paper, we conducted evaluation experiments using the experimental materials shown in 2.2. In the experiments, we used Leave-one-out Cross Validation to discuss the performance of the proposed method. The parameters of MBDF were determined by preliminary experiment.

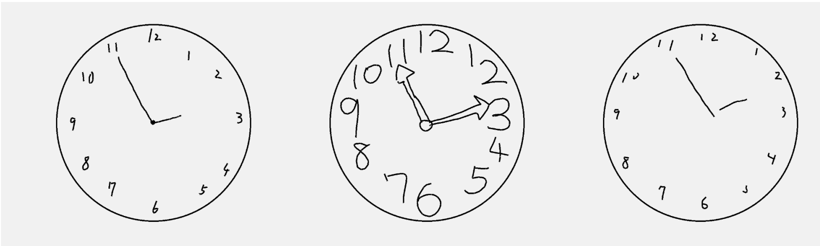

Fig. 8. Examples of Mis-recognition in normal cases

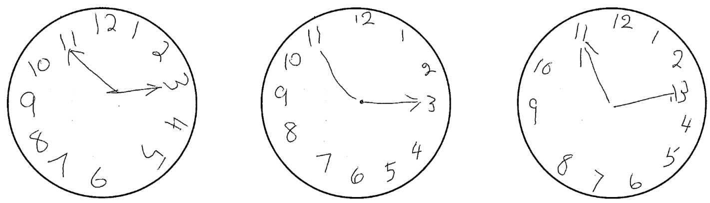

Fig. 9. Examples of Mis-recognition in abnormal cases

4.1. Classification Accuracy

Table 2 shows the summarized experimental results and Table 3 does recognition accuracies in the cases of two-class (Normal vs. Dementia) and four-class (Normal vs. VaD vs. AD vs. MCI) classification, respectively. In the case of two-class classification, sensitivity and specificity are 0.94 and 0.82, respectively. It seems that the proposed method has sufficient performance for practical use.

Fig. 8 and Fig. 9 show examples of mis-recognition cases. In the case of Fig. 8, the size of the digits and the shape of the clock hands are quit different. This made the feature vector change drastically. As a result, these images were not classified properly. In the case of Fig. 9, the proposed method recognized them as normal case even though they were dementia cases. As you can see, it is difficult even for human to recognize them as dementia case because they do not have significant differences from normal cases. To recognize them properly, additional information, such as pen strokes, would be required. Of course, it is sometimes difficult to classify them into four classes.

In Bennasar *et al.* [10], the classification accuracy for two category classification normal and abnormal was 89.37% and for four category 68.62% using single stage classifier, and the value was higher than that of the proposed method. However, the authors regarded VaD and AD as one class while in this paper VaD and AD are classified separately that make the classification more challenge. On the other hand, the classification was done using 48 features developed by the authors while in our approach only the directional feature has been used which reveal the effectiveness of our proposed feature extraction method. Of course, we cannot compare the performances of the conventional and proposed method fairly. But the performance of the proposed method seems not so low and to have a certain level of effectiveness.

Table 2. Recognition results of each symptom

		Recognition Result (k=15)				Total of Images
		Normal	VaD	AD	MCI	
Test Image	Normal	90	10	8	2	110
	VaD	2	16	12	7	37
	AD	3	23	23	6	55
	MCI	1	3	2	2	8

Table 3. Summary of classification accuracies

	# of Trials	# of Success Cases	Classification Accuracy
Two Category	210	184	87.6 %
Four Category	210	131	62.4 %

4.2. Recognition Accuracy vs. k

Fig. 10 shows the relationship between recognition accuracy, indexes of Sensitivity and Specificity, and parameter *k* of MBDF. In the discriminant function, the parameter means the number of eigenvalues used in the function. As you can see, the sensitivity was improved and saturated when *k* was large. On the other hand, specificity was worsened and so was accuracy. The obtained results indicate that the performance of the proposed method depends on the value of *k*, and the value of *k* should be determined properly to obtain the best classification performance. At the moment, we do not have sufficient know-how to determine the value automatically or determine it by preliminary experiments. More investigations and discussions about this point would be required to improve the performance of the proposed method.

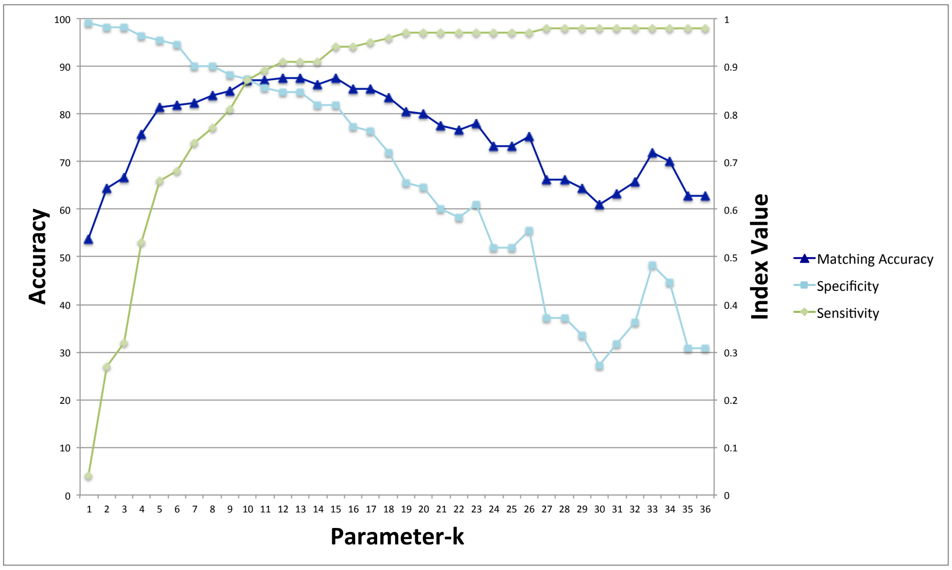

Fig. 10. Recognition Accuracy vs. *k*

5. Conclusion

This paper proposed a classification method for a Clock Drawing Test. We employed a Weighted Direction Index Histogram method and a Modified Bayesian Discriminant Function for classification. Drawing produced by healthy/dementia persons were corrected and these were employed in the evaluation experiment. As a result of the experiments, the proposed method could classify 87.6% of the input images appropriately. In addition, we also discussed the relationship and dependency between recognition accuracies and the parameter *k* of MBDF.

This project has only just begun. Another dividing method will be required to improve classification accuracy of the proposed method. In addition, we will discuss a new evaluation method using online drawing data.

Acknowledgements

This research was supported by the Ministry of Education, Science, Sports and Culture, Grad-in-Aid for Scientific Reseach (C) 26750222, 2015.

References

1. Ministry of Health, Labour and Welfare of Japan, http://www.mhlw.go.jp
2. M. Kanoh, Y. Oida, Y. Nomura, A. Araki, Y. Konagaya, K. Ihara, T. Shimizu and K. Kimura, "Examination of Practicability of Robot Assisted Activity Program using Communication Robot for Elderly People", Journal of Robotics and Mechatronics, vol. 23, No. 1, pp. 3-12, 2011
3. ifoo Co., Ltd, http://www.ifoo.co.jp
4. Y. Izutsu, H. Kawanaka, K. Yamamoto, K. Suzuki H. Takase and S. Tsuruoka, "A Study on Conversational Content Recogni- tion Method Using Japanese WordNet for Robot-Assisted Therapies", Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 16, No. 1, pp. 62-68, 2012
5. Y. Izutsu, R. Sumiyoshi, H. Kawanaka, K. Yamamoto, H. Takase and S. Tsuruoka, "A Proposal of Dementia Evaluation Method Using Interaction with Communication Robots in Welfare Facilities", Journal of Japan Association for Medical Informatics, Vol. 32, No. 2, pp. 73-81, 2012
6. H. Nagasaka, H. Kawanaka, K. Yamamoto, K. Suzuki, H. Takase and S. Tsuruoka, "Development of Dementia Evaluation System Using Daily Conversations", Proc. of Fuzzy System Symposium, Vol. 28, pp. 739-742, 2012
7. H. Kajiwara, H. Kawanaka, K. Yamamoto, H. Takase and S. Tsuruoka, "Modified Weighted Direction Index Histogram Method for Schema Recognition", Lecture Notes in Computer Science (GREC2013 - Graphics Recognition: Current Trends and Challenges), B. Lamiroy and J. Ogier (Eds.) Springer, ISBN 978-3-662-44853-3, pp. 63-73, 2014
8. T. Shigemori, H. Kawanaka, H. Takase and S. Tsuruoka, "Development of Dementia Evaluation System Using Conversations and Drawing Tests",Proc. of the 6th International Workshop on Regional Innovation Studies (IWRIS2014), pp. 43-46, 2014
9. M. Bennasara, R. Setchi, A. Bayerb, Y. Hicks, "Feature Selection Based on Information Theory in the Clock Drawing Test", Proc. of the 17th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems, pp. 456-465, 2013
10. M. Bennasar, R. Setchi, Y. Hicks, "Cascade Classification for Diagnosing Dementia" Proc. of the 2014 International Conference on Systems, Man, and Cybernetics, pp. 2535-2540, 2014
11. Davis R, Libon DJ, Au R, Pitman D, Penney DL. Think, "Inferring cognitive status from subtle behaviours", the 26th IAAI Conference, 2898-905, 2014
12. Open-Sorce Large Vocabulary CSR Engine Julius, http://julius.sourceforge.jp/
13. F. Kimura, T. Wakabayashi, S. Tsuruoka, Y. Miyake, "Improvement of handwritten Japanese character recognition using weighted direction code histogram", Pattern Recognition, vol. 30, no. 8, pp. 1329-1337, 1997
14. S. Tsuruoka, M. Kurita, T. Harada, F. Kimura, Y. Miyake, "Handwritten KANJI and HIRAGANA Character Recognition Using Weighted Direction Index Histogram Method", The Transactions of the Institute of Electronics, Information and Communication Engineers, Vol. J70-D, No. 7, pp. 1390-1397, 1987
15. S. Tsuruoka, H. Morita, F. Kimura, Y. Miyake, "Handwritten Character Recognition Adaptable to the Writer", Procs. of IAPR Workshop on Computer Vision - Special Hardware and Industrial Applications (MVA1998), pp. 179-182, 1988