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Dementia Detection Using Weighted Direction Index Histograms and SVM for Clock Drawing Test

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Abstract

Increasing the number of elderly persons who have dementia is one of the severe social problems. In Japan, the Ministry of Health, Labor and Welfare expects that the number of dementia patients will be around 5 million in 2025. It is also easily estimated that they require various living supports. Therefore, early detection and prevention of dementia are important. The authors have been developing a new system for quantitative and accurate evaluation of dementia. The basic concept of our system is evaluating a patient's dementia types and progression without awareness. To realize this, we are now developing the system using daily conversations, drawings, facial expressions and so on. In this paper, we focused on Clock Drawing Test (CDT) and proposed a dementia evaluation method for CDT. In the proposed method, Weighted Direction Index Histogram Method was used to extract features from given images, and Support Vector Machine (SVM) detected dementia cases from them. As a result of evaluation experiments, the proposed method could detect 97.1% of dementia cases correctly.

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Keywords: Dementia Evaluation, Clock Drawing Test, Weighted Direction Index Histogram, Support Vector Machine

1. Introduction

Increasing the number of elderly persons who have dementia is one of severe social problems[1]. According to the article published by the Ministry of Health, Labor and Welfare of Japan, the number of elderly persons with dementia will be around 5 million in 2025. It is also easily estimated that the number of dementia patients who need living supports has also been increasing in Japan[2]. Therefore, early detection and prevention of dementia are important.

There are many dementia types, and they can be categorized into subtypes based on their symptoms, *e.g.* disorder of memory, orientation, calculations, learning and language abilities and so on[3,4,5]. Dementia patients require various living supports based on their symptoms to keep their Quality Of Life (QOL). Welfare facilities often conduct dementia check-tests to detect dementia and monitor its progression. The tests consist of various small tests based on

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orientations. By using the check-tests continuously, we can evaluate subtypes and progression of dementia by aging variation. From viewpoints of medical and welfare science, it is important to conduct the check-tests continually. Some elderly persons are, however, often very nervous about the tests. As a result, the tests cannot be done accurately. For doing the check-tests accurately and continuously, these tests should be conducted without awareness.

In this study, we aim to develop a new system for quantitative and accurate evaluation of dementia. The basic concept of out system is evaluating a patient's dementia types and its progression without his/her awareness. To realize this, we use not only daily conversations but also line drawings, facial expressions and so on. In this paper, we focus on Clock Drawing Test (CDT), which is one of drawing tests for dementia evaluation, and propose a new assessment methodology for CDT. In the proposed method, Weighted Direction Index Histogram Method[6,7,8] is used to generate a feature vector from a given drawing. Support Vector Machine (SVM) detects dementia with the generated feature vector.

The organization of this paper is as follows. Section 2 introduces the previous works for robot-assisted therapies and dementia evaluation systems. Section 3 shows how to collect experimental materials and their features. Section 4 shows the detail procedures of features extraction and dementia detection methods. In section 5, we show the obtained results and discuss the effectiveness of the proposed method. Finally, section 6 summarizes this paper and describes remained works of the proposed method.

2. Related Works

Currently, many studies on robot-assisted therapies have been reported to prevent and alleviate of dementia. For instance, Kanoh *et al.* developed a robot-assisted therapy system with a conversation robot[9]. In the literature, the robot shown in Fig. 1[10] was used to make simple conversations and do quizzes with dementia patients. This system looks unique and exciting. However, the provided contents have already fixed, and the system cannot give various materials to users. Besides, we cannot evaluate a patient's dementia with the system because the system was developed for dementia prevention only.

To realize the check-tests without their awareness, our colleagues had discussed dementia evaluation methods using a conversation robot instead of a medical doctor or facility staff. Izutsu *et al.* discussed a conversational content recognition method using a concept dictionary[11]. He also proposed a dementia evaluation technique using daily conversations and conducted evaluation experiments with facility staffs to discuss the effectiveness of his method[12]. Nagasaka *et al.* proposed a method to control conversational topics for dementia evaluation with daily conversations[13]. These methods, however, were not ready for practical use because they could evaluate time/geographical orientation and short-term memory only. Other orientations and functions are also required for accurate dementia evaluation.

On the other hand, Mohamed *et al.* discussed a dementia diagnosis method for Clock Drawing Test[14,15]. They selected powerful features for dementia diagnosis using Clock Drawing Test[14]. He also proposed the cascade classifi-

Fig. 1. Conversation Robot "ifbot"

cation method for diagnosing dementia [15]. In the method, the effective features based on information theory and some classifiers were employed.

3. Experimental Materials

A sufficient number of images is required for analysis. In this study, the CDT system for tablet terminals was developed to collect clock drawings. Figure 2 shows the developed system by the authors. By using the system, not only images but also their stroke data, *i.e.* time series data, can be obtained. The received stroke data also have the time when the stylus is touched.

In the data collection, the subject was first asked to draw a clock that indicates 2:55 p.m. And then, the subject drew a clock drawing according to instruction. The collected images were used as experimental materials (Fig. 3).

Clock drawing test using the developed system was done to obtain drawings given by healthy persons. In this paper, we collected 110 clock images, which was provided by students and faculty staffs at Mie University. Besides, 100 samples of dementia case were supplied by Cardiff University School of Engineering. Figure 4 shows examples of collected images. As you can see, the features of dementia cases are different from those of healthy cases. The details of the image set are as shown in Table 1. In this paper, we use the experimental material that came from two countries, *i.e.* Japan and the United Kingdom. Features of dementia symptoms do not depend on countries, and the materials will not give a serious effect to experimental results. The authors are also now collecting dementia cases with facility staffs in Japan.

Table 1. Summary of Given Dementia Images.

Dementia Types	Number of Given Images
Vascular Dementia (VaD)	37
Mild Cognitive Impairment (MCI)	8
Alzheimer's Disease (AD)	55

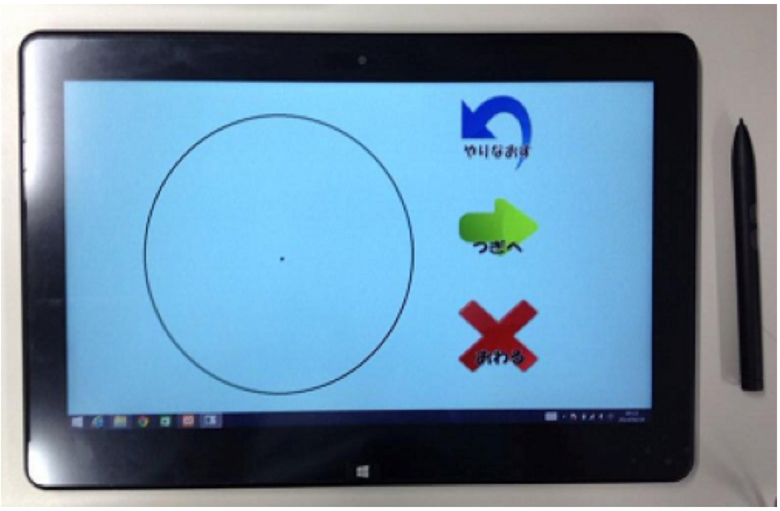

Fig. 2. Clock Drawing Test System Using Tablet Device

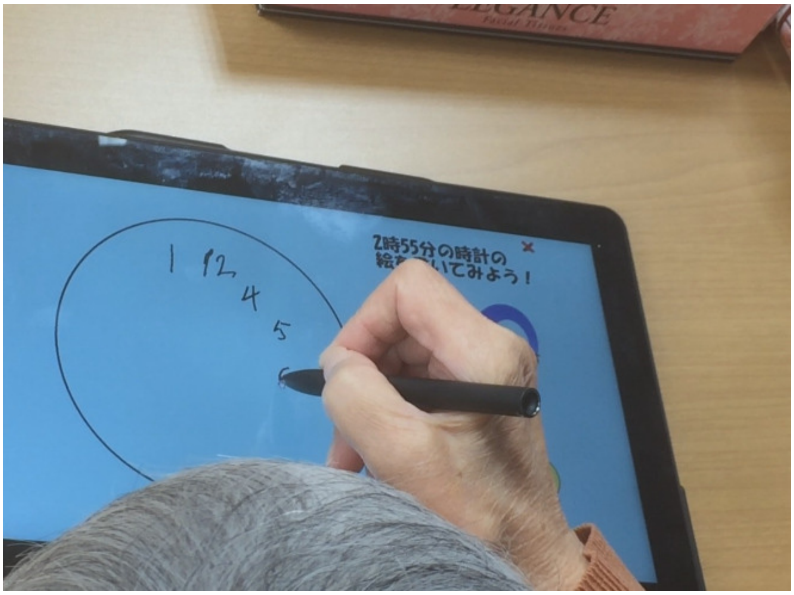

Fig. 3. Data Collection in Welfare Facilities

(a) Healthy Cases

(b) Demantia Cases

Fig. 4. Examples of Employed Images

4. Methods

4.1. Feature Extraction for Clock Drawing Test

In this study, we use Weighted Direction Index Histogram (WDIH) method. This method is one of feature extraction methods considering shapes of the input image and often used in commercial OCR software, automatic sorting machines for postal items and so on. This paper focuses on that the features of the given drawings are quite similar to those of handwritten characters, and we employ the method to generate a feature vector.

Figure 5 shows the outline of the WDIH method. The method first divides the input image into 49, *i.e.* 7×7, sub-regions. After this, the contour of the image in each sub-region is traced and then, the direction index histogram with chain codes is generated. The generated histograms reflect contour shapes of the image in each sub-region, and it will be work well for dementia detection.

Next, the spatial weighted-filter based on Gaussian distribution is applied to the histograms for reduction of dimension. Fig. 6 shows the outline of the Gaussian filter and its application. In this process, the center of the filter is put on the marked sub-regions and then, the weighted histogram is obtained. We apply this process to all marked sub-regions, and finally, a feature vector is generated by the converted histogram values. The parameters of the filter are determined based on the literature[7]. By this process, the 49 sub-regions are converted to 16 (4×4) sub-regions. Finally, a feature vector is generated by using the converted histogram values.

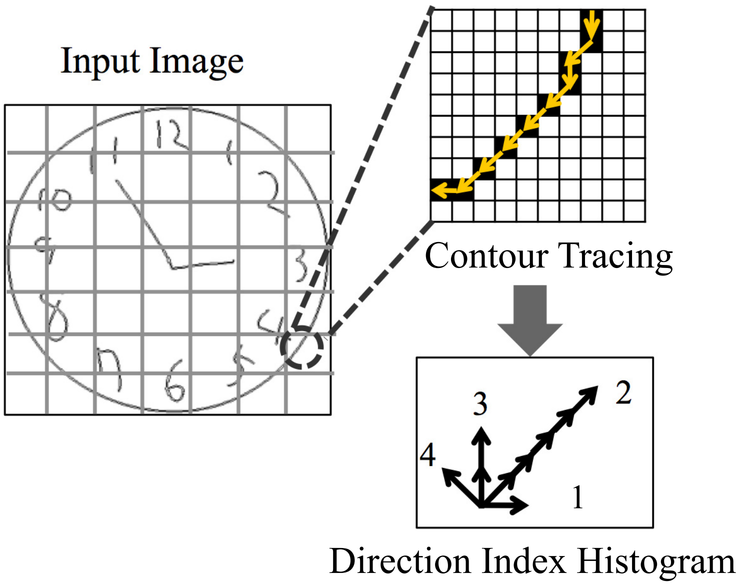

Fig. 5. Generation of Direction Index Histogram Method

4.2. Dementia Detection with SVM

This paper uses Support Vector Machine to detect dementia cases from the given drawings. Support Vector Machine (SVM) is well known as a 2-categories pattern recognition method, and it can be expanded to a non-linear discriminant method by combining the kernel learning based on the optimal separating hyperplane[16].

For classification of them, the optimal separating hyperplane is determined by the parameters, σ and cost C. The classification performance of SVM heavily depends on these parameters. In this paper, we use the Radial Basis Function (RBF) given by

$$k(x_1, x_2) = -\exp(\frac{||x_1 - x_2||^2}{2\sigma^2}). \tag{1}$$

This function is a typical one and usually used as a kernel for SVM. In the formula, x denotes the data set of each class, and σ does the range of influence of RBF. The parameters for SVM are optimized with Grid-search method.

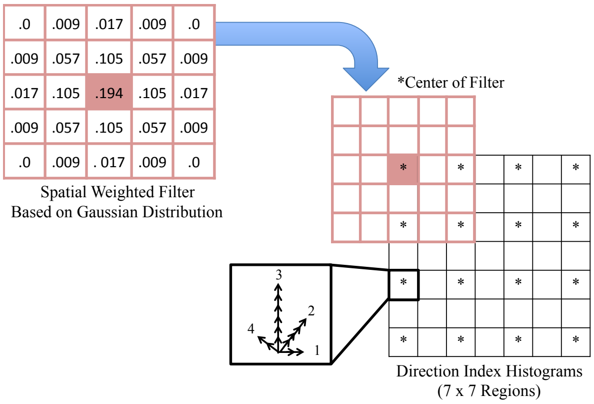

Fig. 6. Application of Weighted Spacial Gaussian Filters

4.3. Determination of Parameters for SVM

Before evaluation experiments, we determined the parameters for SVM. In this paper, we divided the given images into three groups first, and then a grid search technique was applied as follows. Table 2 shows the ranges of the parameters for the grid search. As the first step, the cost parameter C was varied from 1 to 15 and σ was done from 0.1 to 2.0 for a coarse search. In this step, the parameters C_1 and σ_1 were determined. After this, the fine search was done to identify the optimum parameter set. The determined parameters were used for the classifier in the experiments.

Table 2. Grid-search for SVM

Search	Parameter Name	Range	Step Size
Coarse Search	C	1~15	1
	σ	0.1 ~ 2.0	0.1
Fine Search	C	$C_1 \pm 1$	0.1
	σ	$\sigma_1 \pm 0.1$	0.01

5. Evaluation Experiments and Discussion

5.1. Performance of Dementia Detection

Table 3 shows the summarized results of dementia detection. This table shows the relationship between the detection performance and the number of sub-regions in WDIH method. In the table, the underlined and bold highlighted parts mean the maximum accuracy. As the result of the experiments, the detection accuracy of the proposed method was 97.1% when the number of sub-regions was 25 (5×5).

Figure 7 shows the relationship between the detection accuracy and the parameters of SVM. As you can see, when the value of *sigma* was less than 0.3, then the detection accuracy was more than 90%. And it did not depend on the cost parameter C. On the other hand, the detection performance heavily depended on C when *sigma* was large, *e.g.* more than 0.15. In the experiments, we obtained the best detection performance when C and σ were 12 and 0.01, respectively.

Table 3. Classification Accuracy of SVM

# of Sub-regions	Sensitivity	Specificity	Detection Accuracy
4×4	0.96	0.95	95.7%
5×5	**0.97**	**0.97**	**97.1%**
6×6	0.95	0.98	96.7%
7×7	0.89	0.99	93.8%

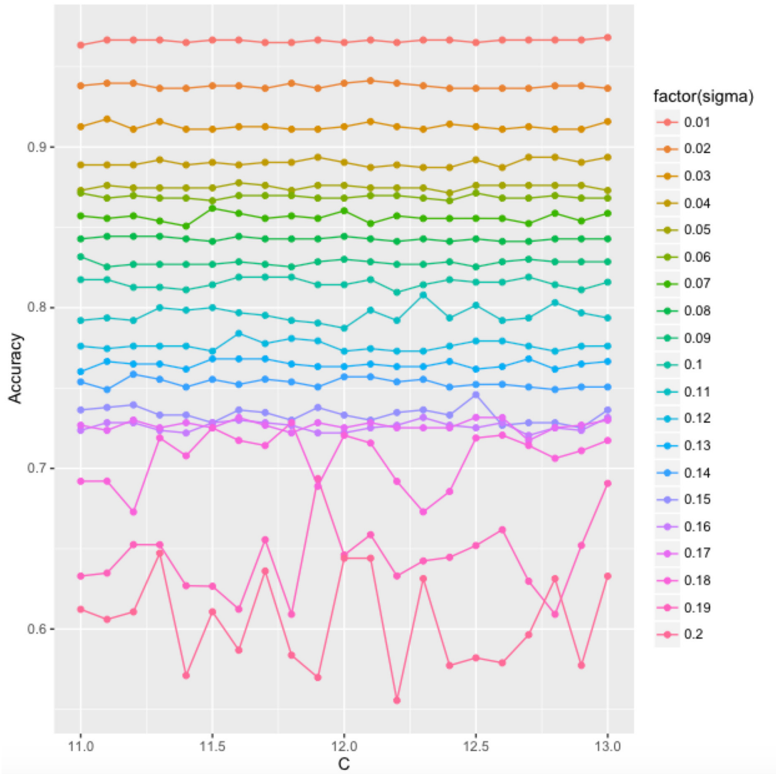

Fig. 7. Relationship between Accuracy and Parameters of SVM

5.2. Discussion

The obtained results indicate that the proposed method with SVM could classify 97.1% of the input images into two categories, *i.e.* Health/Dementia, appropriately. In the case of the previous study, the accuracy of two types classification was 89.37%. As mentioned in the previous section, the WDIH method divides the input image into sub-regions. Thus, the classification performance of the method heavily depends on the number of sub-regions. According to the obtained results, the proposed method performed well when the number of sub-regions was 25 (5×5). When the number of sub-regions is small, we cannot extract features reflecting detailed shapes of the input image. On the other hand, many sub-regions without a pixel will be generated when we divide the input image into many sub-regions. The obtained results indicate that the WDIH method could extract sufficient features for this problem in the case the number of sub-regions was 25.

The obtained results show that SVM was a powerful classifier for two categories classification. In the previous study, we used Modified Bayesian Discriminant Function (MBDF). This function is usually used for multi types classification. From the viewpoint of dementia detection, *i.e.* two categories classification, SVM worked well compared

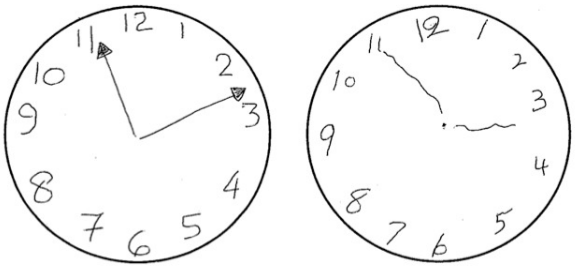

Fig. 8. Mis-recognition Cases of Dementia Image

to MBDF. The proposed method also looks like being ready for practical use. However, the proposed method could not classify some clock drawings correctly.

Figure 8 shows examples of misclassification cases. These drawings were given by dementia patients. As you can see, these images do not look like dementia cases (Fig. 4) even though facility staffs diagnosed them as dementia. The proposed method only use the shapes of objects, *e.g.* digits and clock hands, in the image to generate a features vector; as a result, the proposed method could not classify them correctly. As described the above, medical doctors and facility staffs make a diagnosis based on his/her symptoms totally. If the person does not have a lesion on Visuospatial and Executive functions, the proposed method cannot detect dementia. The performance of the proposed method is enough, but not ready for practical use. Additional information such as pen strokes data will also be required to recognize them correctly.

6. Conclusion

In this paper, we aimed to develop a new method for dementia evaluation, in particular, Visuospatial and Executive function evaluation, using a drawing test. We focused on a Clock Drawing Test (CDT), which was one of drawing tests, and discussed the feature extraction and dementia detection method. In the proposed method, the Weighted Direction Index Histogram (WDIH) method was used to extract features from the drawings. Support Vector Machine (SVM) was used for dementia detection. We conducted evaluation experiments using collected drawings, which was given by healthy/dementia persons. As a result of the experiments, the proposed method could detect 97.1% of dementia drawings correctly, and the obtained accuracy was ready for practical use.

We are also now collecting and analyzing these data to improve the detection performance of the proposed method. However, plenty of actual data will be required for advanced analyses. Also, advanced discussions about the relationship between dementia progression are also required.

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