Master's thesis

A Study on Computer-assisted Dementia Evaluation Using Clock Drawing Test

Tomoaki Shigemori

Division of Electrical and Electronic Engineering
Graduate School of Engineering
Mie University

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

In Japan, preventing and alleviating dementia are key issues. According to the Ministry of Health, Labour and Welfare of Japan, the number of elderly persons with dementia has been increasing (Figure 1.1) and it is also easily estimated that the number of dementia patients who need living supports has been increasing [1]. This trend must be one of the biggest social and medical problems.

Generally, there are many types of dementia and these are roughly categorized into some subtypes based on their symptoms, *e.g.* disorder of memory, orientation, calculations, learning and language abilities. For instance, Parkinson's disease with dementia causes hallucination, delusion and strong drowsiness. In the case of alcoholic dementia, which is generally caused by heavy alcohol intake, does disorder of memory and orientation. As a result, people with dementia require various supports based on their symptoms to keep their Quality Of Life (QOL).

1.2 Previous Studies and their Problems

Recently, 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 using a conversation robot [2]. In the literature, a conversation robot called "ifbot" (Figure 1.2), which was retailed by ifoo Inc [3], was employed to make simple conversations and do quizzes with dementia patients. By using the system, the authors tried to prevent dementia progression in walfare facilities.

On the other hand, many welfare facilities conduct dementia check tests. The tests consist of various tests and they are conducted to evaluate the progression of a patient's dementia. By using the check tests continuously, it is possible to evaluate subtypes and progression of dementia by ageing variation. From a viewpoint of medical and welfare science, conducting the check test continually is so important. However, some elderly

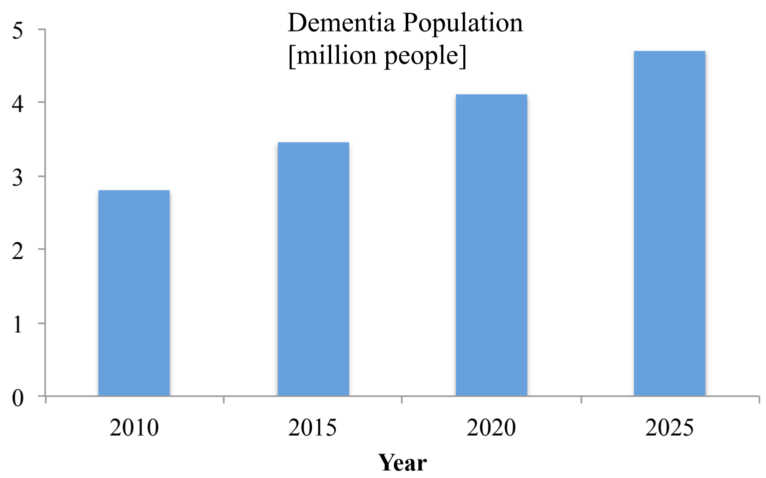


Figure 1.1: Transition of Dementia Population in Japan

persons are often very nervous about the tests and consequently, the tests cannot be conducted accurately. For doing the check tests accurately and continuously, these tests should be conducted without their awareness.

To realize the check tests without their awareness, our research group had discussed a dementia evaluation system using a conversation robot instead of a medical doctor or facility staff. 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 conversational topics by using conceptional structures of nouns. In literature [5], a dementia evaluation technique using daily conversations was proposed and evaluation experiments were conducted in welfare facilities. Nagasaka *et al.* proposed a method to control conversational topics for dementia evaluation with daily conversations [6]. These systems, however, are not ready 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.

1.3 Objective

The final goal of this study is developing a new system for quantitative and accurate evaluation of dementia progression. Figure 1.3 shows a rough image of the project. The basic concept of the system is evaluating a patient's dementia types and progression without his/her awareness. To realize this, this project employs not only daily conversations but also line drawings, facial expressions and so on. Each content is developed to evaluate a specific function/orientation and also input via a tablet device (or measured

Figure 1.2: Conversation Robot "ifbot"

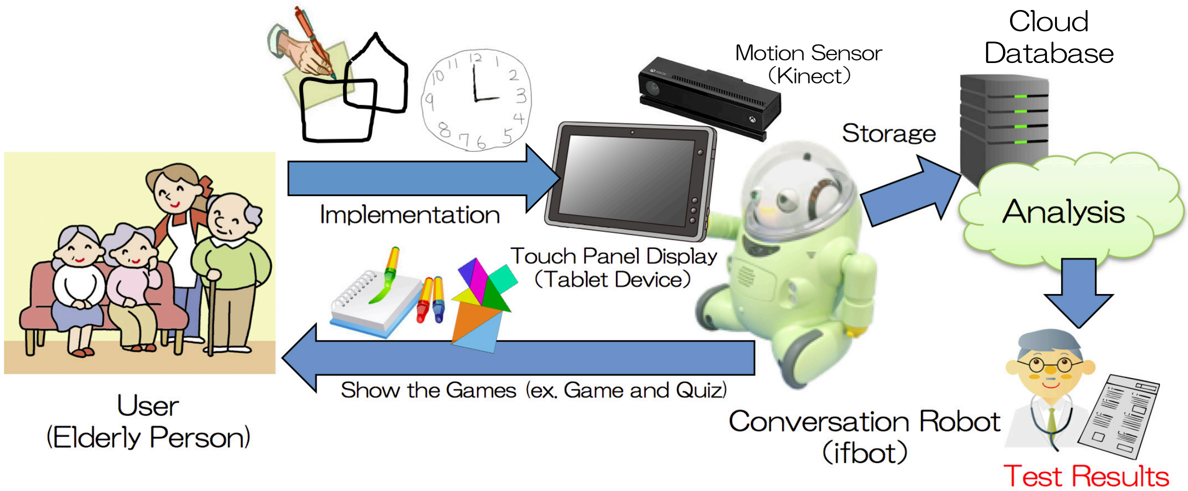


Figure 1.3: Rough Image of our System

by sensors). The obtained data are stored in the database and used for evaluation. By using the stored data, it is expected that accurate dementia evaluation will be realized.

In this thesis, a dementia evaluation method using Clock Drawing Test (CDT), which is a kind of drawing tests, is proposed. In the proposed method, Weighted Direction Index Histogram Method [8–10] is employed to extract features from given line drawings and Support Vector Machine (SVM) detects dementia cases from them. Moreover, Random Forest (RF) is used to classify subtypes of dementia. Evaluation experiments using actual line drawings are conducted to discuss the performance of the proposed method. Moreover, this thesis discusses these classifiers for the dementia evaluation using CDT.

The organization of this thesis is as follows. In Chapter 2, the details of dementia evaluation/prevention techniques are introduced, and their problems are clarified. Chapter 3 shows experimental materials and their features. This chapter also shows the details of feature extraction, dementia detection and dementia type classification methods. In addition, this thesis also shows the outline of other classifiers for discussion. In Chapter 4, experimental results are shown, and the effectiveness of the proposed method is also discussed. Finally, Chapter 5 summarizes the contents of this thesis.

Chapter 2

Dementia Evaluation and its Problems

2.1 Dementia and its Features

Generally, dementia develops due to injury to brain cells, and it makes various functions decrease drastically. According to literature on dementia researches, there are many subtypes of dementia and these are mainly categorized into some types [13]. The followings are examples of subtypes of dementia.

1. Alzheimer's Disease (AD)

2. Vascular Dementia (VaD)

3. Mild Cognitive Impairment (MCI)

For instance, Alzheimer's Disease (AD) occurs with an accumulation of Amyloid β-protein and atrophies a patient's brain. In the early stage of AD, a patient sometimes forgets his/her daily behaviors. When the disease has progressed to Middle-Stage, the ability of "Orientation to Time" is gradually reduced. In other words, the patient loses understanding his/her actions. In addition, the patient also loses the ability of recent memory gradually. Loitering is also one of the typical symptoms of AD. In the case of severe AD, a patient completely forgets the meaning of the words, and cannot have a conversation at all.

Vascular Dementia (VaD) is also one of typical dementia types. Generally, VaD is caused by a cerebrovascular accident like Cerebral Infarction (CI) and Cerebral Bleeding. Because of this mechanism, the symptoms of VaD heavily depend on the part where was damaged by the cerebrovascular accident. Moreover, these cerebrovascular accidents are caused by lifestyle diseases, thus preventing lifestyle diseases is one of the most important factor to prevent VaD.

Mild Cognitive Impairment (MCI) is not a severe case of dementia, but in a condition in which a patient has minor problems on his/her cognition functions. In most MCI cases, a patient does not need living supports. Generally, 50% of MCI patients progress to dementia within 5 years. By doing various medication such as training and rehabilitation in the early stage of dementia, it is possible to alleviate these symptoms.

As mentioned above, symptoms of dementia heavily depend on disease types, injured part(s) in the brain and a patient's lifestyle. For caring the dementia patients, medical (or welfare facility) staffs have to understand them well for sufficient caring. However, similar symptoms also occur due to other illness or a side effect even if the subject does not have dementia. Therefore, distinctions between these actions and dementia are also important to care and alleviate a disease.

2.2 Dementia Evaluation in Welfare Facilities

Many welfare facilities use dementia check tests, which consist of various tests. Each check test evaluates a desired function/orientation of a patient. Therefore, combining plural check tests is so important to evaluate a patient's dementia and its type correctly. By using the check test continuously, we can evaluate a patient's dementia type and observe its progression as the time series data (aging variation data). Moreover, the obtained results can be used to improve the patient's Quality Of Life. In the fields of medical and welfare sciences, it is important to conduct the check test continually.

2.2.1 Revised Hasegawa's Dementia Scale

Revised Hasegawa's Dementia Scale (HDS-R) has been widely used for dementia evaluation in welfare facilities [12]. Generally, this screening test consists of 9 simple questions with a maximum score of 30 (Table 2.1). These questions measure some subject's function, *e.g.* time orientation, geographical orientation, immediate and recent Memories and so on. In general, if a person gets a score of less than 30, then the person has a strong possibility of dementia.

2.2.2 Mini Mental State Examination

Mini-Mental State Examination (MMSE) is one of dementia check tests proposed by Folstein in 1975, which is well known all over the world [14]. This test consists of 11 questions and marks out of 30 based on orientations, calculation ability, memory, language ability and graphic recognition ability. Table 2.2 shows the detail of MMSE. Almost of the questions are similar to HDS-R in 2.2.1. MMSE can evaluate the others functions/orientations in addition to those evaluated by HDS-R. For instance, we can evaluate Spatial Ability and Executive Function by using the line drawing given by a subject (Question 11, Figure 2.1). By using these results, the subject can be classified

Table 2.1: Revised Hasegawa's Dementia Scale (HDS-R)

Question (1) How old are you? (1 point)
Question (2) What is the year? month? data? day? (1 point each)
Question (3) What is this place? (2 points, if give a hint : 1 point)
Question (4) Pronounce the three words slowly one by one. After a few minutes, ask the subject to repeat them. (1 point each)
Question (5) Subtract 7 from 100. (If correct, 1 point. If not, skip to Question 6) Subtract -7 from it again. (If correct, 1 point)
Question (6) Repeat 6 - 8 - 2 backwards. (If not, skip to Question 7) Repeat 3-5-2-9 backwards. (1 point each)
Question (7) Recall the three words you pronounced before. (2 points each. If give a hint: 1 point each)
Question (8) Show five unrelated common objects and take them back. Then ask for recalling. (1 point each)
Question (9) Name all vegetables that come to mind. (0 $\sim$ 5 vegetable (s): 0 point) (6 $\sim$ 10 vegetables: 1 $\sim$ 5 points)

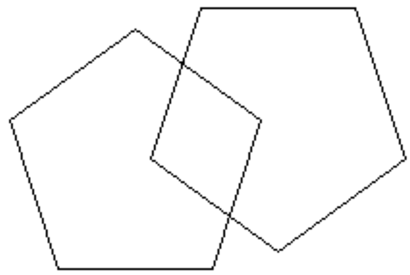


Figure 2.1: Sample Image for 11th Question

into some types based on the subject's symptoms. There are some criteria for evaluation and Table 2.3 shows some of them.

2.2.3 Drawing Tests

Drawing Test is one of check 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, a facility staff gives writing materials to an elderly person, and then the person is instructed to draw a graphic image, usually of a clock. The 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 sometimes make the elderly person nervous. To overcome this problem, the tests should be conducted without the subject's awareness of being tested.

Figure 2.2 shows examples of clock drawings given by patients. As you can see, features of the images are heavily influenced by disease progression and types. Therefore, many studies on Clock Drawing Test have been reported [15–17]. For instance, Mohamed *et al.* proposed a feature selection method based on Feature Interaction Maximization (FIM) [15]. 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 also presented a novel cascade classifier for diagnosing dementia by classifying clock images. The number of drawings was relatively high compared similar studies [16].Randall *et al.* proposed a Digital Clock Drawing Test, which is CDT 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 developed a training program for technicians who administered the test and classify strokes [17].

Table 2.2: Mini-Mental State Examination (MMSE)

Question (1) What is the year? Season? Date? Day? Month? (1 point each)
Question (2) Where are we now? State (Province/Prefecture)? Country? Town/City? Hospital? Floor? (1 point each)
Question (3) Pronounce the three words slowly one by one. After a few minutes, ask the subject to repeat them. (1 point each)
Question (4) Subtract 7 from 100. (If correct, 1 point. If not, skip to Question 5). Subtract -7 from it again. (until 5 times)
Question (5) Recall the three words you pronounced before. (1 point each)
Question (6) Show the patient two simple objects (ex. a wristwatch, a pencil). Then, ask the patient to name them. (2 points each, if give a hint, 1 point each)
Question (7) Repeat the phrase. (1 point)
Question (8) Take the paper in your right hand, fold it in half, and put it on the floor. (The examiner gives the patient a piece of blank paper, 1point each)
Question (9) Please read this and do what it says. (Written instruction is ”Close your eyes”. 1 point)
Question (10) Make up and write a sentence about anything. (This sentence must contain a noun and a verb. 1 point)
Question (11) Please copy this picture. (Fig. reffig:MMSE) (All 10 angles must be present and two must intersect. 1 point)

Table 2.3: Interpretation of the MMSE

Method	**Score**	**Interpretation**
Single Cutoff	<24	Abnormal
Range	<21	Increased odds of dementia
	>25	Decreased odds of dementia
Education	21	Abnormal for 8th grade education
	<23	Abnormal for high school education
	<24	Abnormal for college education
Severity	24-30	No cognitive impairment
	18-23	Mild cognitive impairment
	0-17	Severe cognitive impairment

2.3 Problems in Evaluation Methods

Currently, these tests are conducted in hospitals and welfare facilities. However, these tests are generally conducted face to face and give the subjects awareness. Therefore, a dementia evaluation method without awareness must be required for accurate evaluation. Moreover, evaluation criteria heavily depend on knowledge and experiences of examiner, *i.e.* medical doctors and facility staffs. In particular, a quantitative assessment for the CDT has not been established. The automatic evaluation method for the quantitative assessment is required.

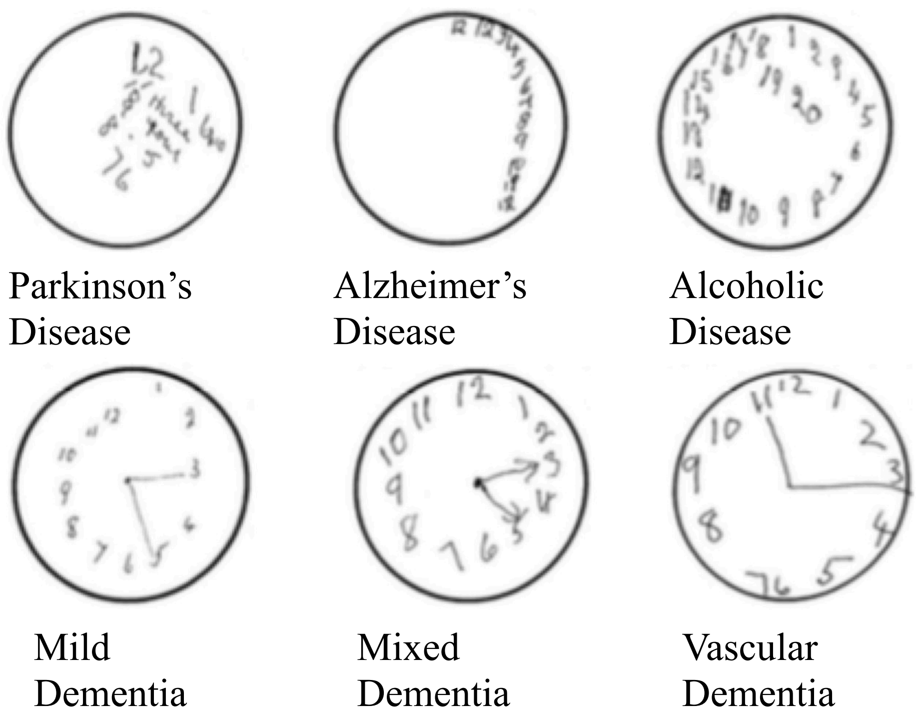


Figure 2.2: Examples of Clock Drawing Test (Dementia Cases)

Chapter 3

Classification Method for CDT

3.1 Experimental Materials

Generally, a sufficient number of drawing images is required for analysis. In this study, the CDT system for tablet devices was developed to collect clock drawings. Figure 3.1 shows the developed system. By using the system, clock drawings and their stroke data, *i.e.* time series data, can be obtained. The obtained stroke data also have the times when the stylus is touched.

In the experiment, 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 an instruction. The collected images were used as experimental materials. For control images (healthy cases), a clock drawing test using the developed system was conducted by students at Mie University,

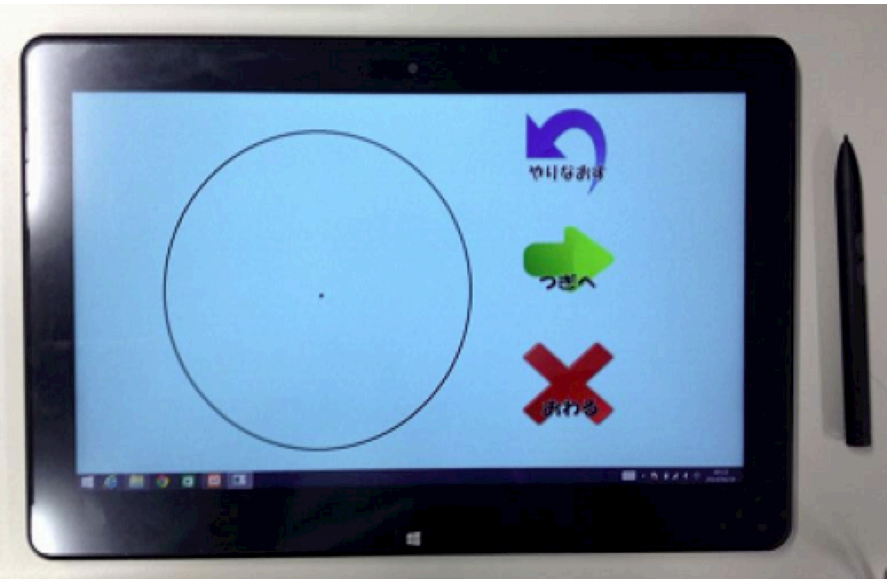
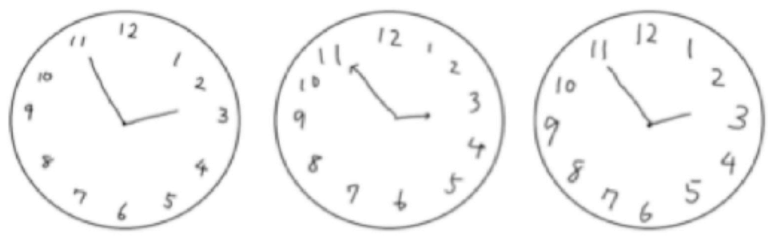
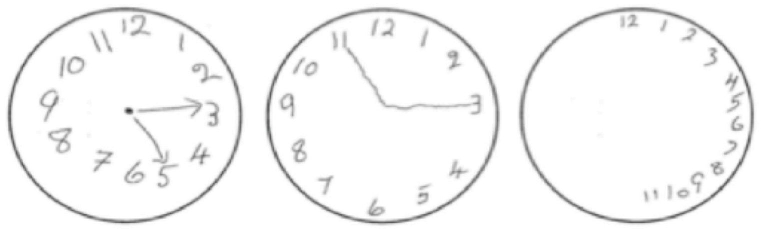


Figure 3.1: Clock Drawing Test System Using Tablet Device



(a) Healthy Cases



(b) Demantia Cases

Figure 3.2: Examples of Employed Images

Table 3.1: Summary of Dementia Images

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

and 110 clock drawings were obtained. In addition, 100 clock drawings of dementia case were given by Cardiff University. Figure 3.2 shows examples of collected images. The details of the image set are as shown in Table 3.1.

3.2 Proposed Method

The objective of this study is

1. Detecting Dementia and
2. Classifying Dementia Type

using clock drawings. As the first step, binarization, noise reduction, and normalization were applied to the input images as prepossessing. After this, a feature vector was

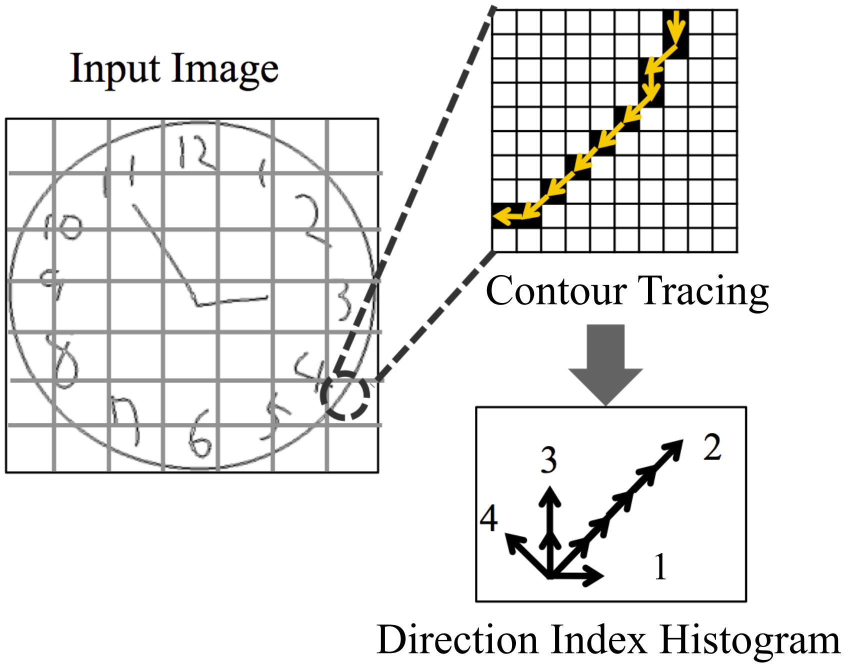


Figure 3.3: Application of Weighted Direction Index Histogram Method

generated by using Weighted Direction Histogram method, which was proposed by literature [8–10]. In this study, Support Vector Machine (SVM) and Random Forest (RF) were used for dementia detection and dementia types classification, respectively.

3.2.1 Feature Extraction Using Weighted Direction Index Histogram

Weighted Direction Index Histogram (WDIH) is one of the feature extraction methods used in commercial OCR engines. Figure 3.3 illustrates a rough image of the WDIH method. In the method, the input image is first divided into 49 sub-regions (7×7 grids). 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 determines the parameters of the filter based on the literature [9]. By this process, the sub-regions are converted to 16 (4×4) sub-regions. Finally, a feature vector is generated by using the histogram values of the converted sub-regions.

3.2.2 Dementia Detection Method Using Support Vector Machine

Support Vector Machine (SVM) is a kind of pattern recognition methods [19]. SVM was expanded to a non-linear discriminant method by combining the kernel learning based on the optimal separating hyperplane [19]. This method is well-known as the best discriminator for 2categories classification. For classification of them, the optimal separating hyperplane is determined by the following parameters, *i.e.* σ and cost C. The classification performance of SVM heavily depends on these parameters. In this thesis, Radial Basis Function (RBF) given by

$$k(x_1, x_2) = -\exp(\frac{||x_1 - x_2||^2}{2\sigma^2}) \tag{3.1}$$

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

3.2.3 Dementia Type Classification Using Random Forest

Random Forest (RF) is one of bagging tools [18] and consists of decision trees. Figure 3.4 shows the rough sketch of Random Forest. In RF, m sub-dataset are first generated by using a random sampling method, *i.e.* Bootstrap Sampling. Next, RF generates m

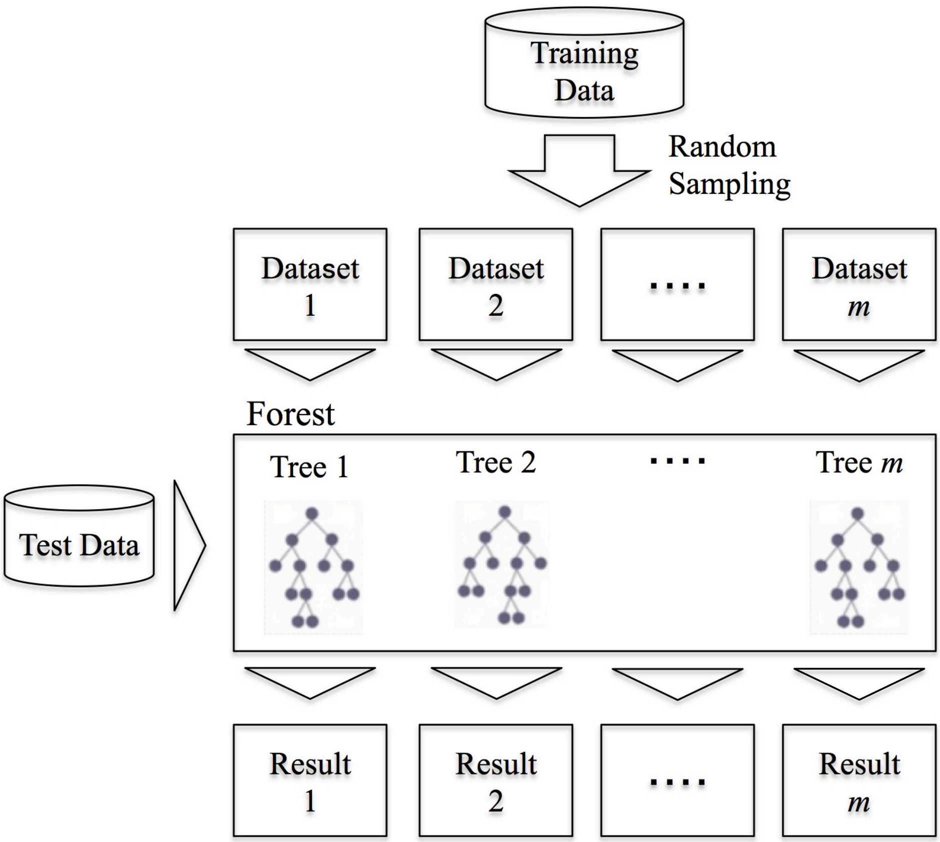


Figure 3.4: Rough Image of Random Forest

decision trees with these data sets, *i.e.* these data are used as training data for the trees. By using the above procedure, we can generate trees that have low correlation each other. For classification, RF uses these trees as weak classifiers and finally outputs result by using majority voting of classification result given by the trees. In this study, the parameters of RF, *i.e.* explanatory variables for random sampling, are determined by a grid search method.

3.2.4 Modified Bayesian Discriminant Function

Modified Bayesian Discriminant Function (MBDF) is often used for hand-written character recognition with WDIH [8,9]. It is expected that the method has the capability to recognize clock images accurately. The definition of MBDF is given by

$$g(x) = \sum_{i=1}^{k} \frac{\{{}_l\varphi_i{}^T(x - {}_l\,\mu)\}^2}{{}_l\lambda_i} + \sum_{i=k+1}^{n} \frac{\{{}_l\varphi_i{}^T(x - {}_l\,\mu)\}^2}{{}_l\lambda_{k+1}} + \ln\left(\prod_{i=1}^{k} {}_l\lambda_i \cdot \prod_{i=k+1}^{n} {}_l\lambda_{k+1}\right) \tag{3.2}$$

where x denotes the n-dimensional feature vector for the input image, and ${}_l\mu$ does the average vector of clock drawings l in the dictionary. ${}_l\lambda_i$ and ${}_l\varphi_i$ are the i-th eigenvalue and eigenvector of the drawing 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 drawing in the dictionary. This proposed method outputs a category, *i.e.* AD, VaD, MCI or Normal, with the smallest dissimilarity as a recognition result.

Chapter 4

Results and Discussions

4.1 Performance of Dementia Detection

In this paper, evaluation experiments were conducted. In the experiments, the materials shown in 3.1 were used materials. The parameters for each method were preliminarily determined with a grid-search method, and Leave-one-out Cross Validation were used to discuss the performance of the proposed method.

Table 4.1 shows the summarized experimental results using SVM. This table 4.1 shows the relationship between classification performance and the number of sub-regions in WDIH. In the table, the underlined and bold highlighted parts mean the maximum accuracy. As the result of experiments, the classification accuracy of the proposed method was 97.1% when the number of sub-regions was 25 (5×5).

Figure 4.1 shows the relationship between classification accuracy and the parameters of SVM. In the experiment, the optimum values for the parameters were determined in two stages, and each range of parameters is shown in Table 4.2. In the first stage, C was ranged from 1 to 15 and σ was done from 0.1 to 2.0 for coarse search. In this phase, the parameters C_1 and σ_1 were determined by coarse search. After this, the fine search was done to determine the optimum parameter values. As you can see, this figure indicates that the classification performance of SVM was the best when C and σ were 12 and 0.01.

Table 4.1: Classification Accuracy of SVM

Classifier	# of Sub-regions	Sensitivity	Specificity	Detection Accuracy
SVM	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%

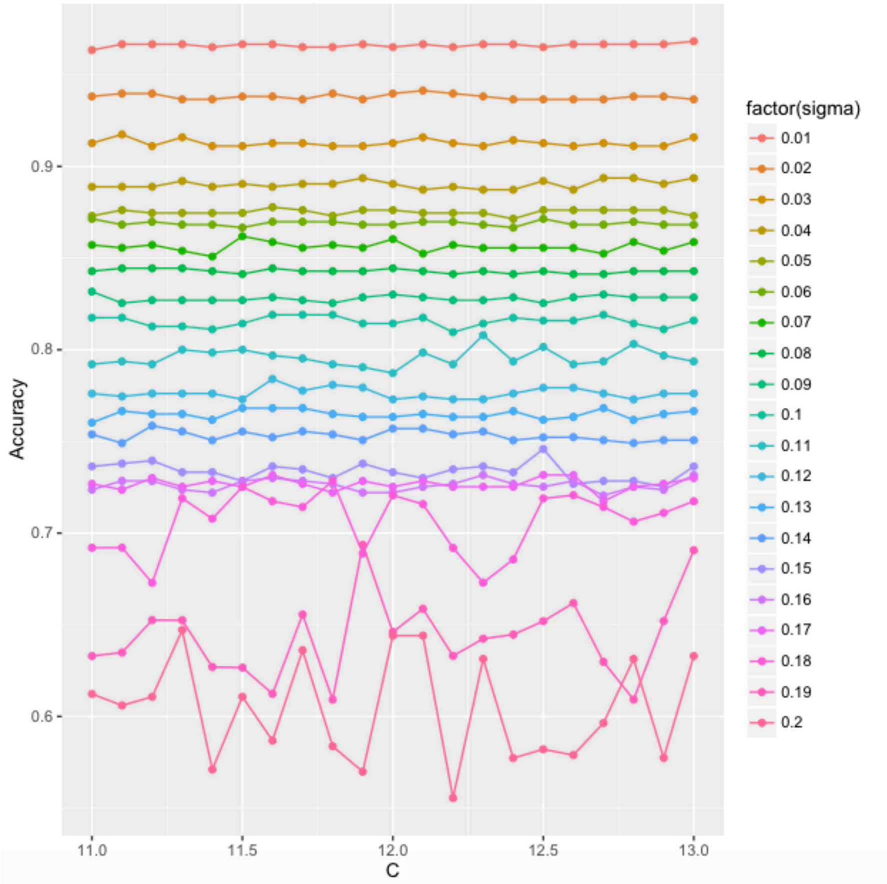


Figure 4.1: Relationship between Accuracy and Parameters of SVM

Table 4.2: Grid-search for SVM

Search	Parameter	Range	Step size
Coarse Search	C	1∼15	1.0
	σ	0.1∼ 2.0	0.1
Fine Search	C	$C_1 \pm 1$	0.1
	σ	$\sigma_1 \pm 0.1$	0.01

4.2 Performance of Dementia Types Classification

This thesis also conducted evaluation experiments for dementia types classification using Random Forest. Table 4.3 shows the summarized experimental results of dementia types classification. This table shows the relationship between classification accuracy and the number of sub-regions in WDIH. In the table, the underlined and bold highlighted parts mean the maximum accuracy. We can see that the classification accuracy of the proposed method was 53.0% when the number of sub-regions was 49 (7×7). Figure 4.2 shows the relationship between classification accuracy and the number of explanatory variables for random sampling (*mtry*). In this experiment, the number of sub-trees were set to 10000, and the value of *mtry* was determined by using grid-search method. This figure indicates that the classification performance of RF was the best when *mtry* was 163.

Table 4.3: Result of Dementia Types Classification

# of sub-regions	AD	MCI	VaD	Classification Accuracy
4×4	7/55	0/8	4/37	51.0%
5×5	37/55	0/8	7/37	72.9%
6×6	40/55	0/8	7/37	47.0%
7×7	**41/55**	**0/8**	**12/37**	**53.0%**

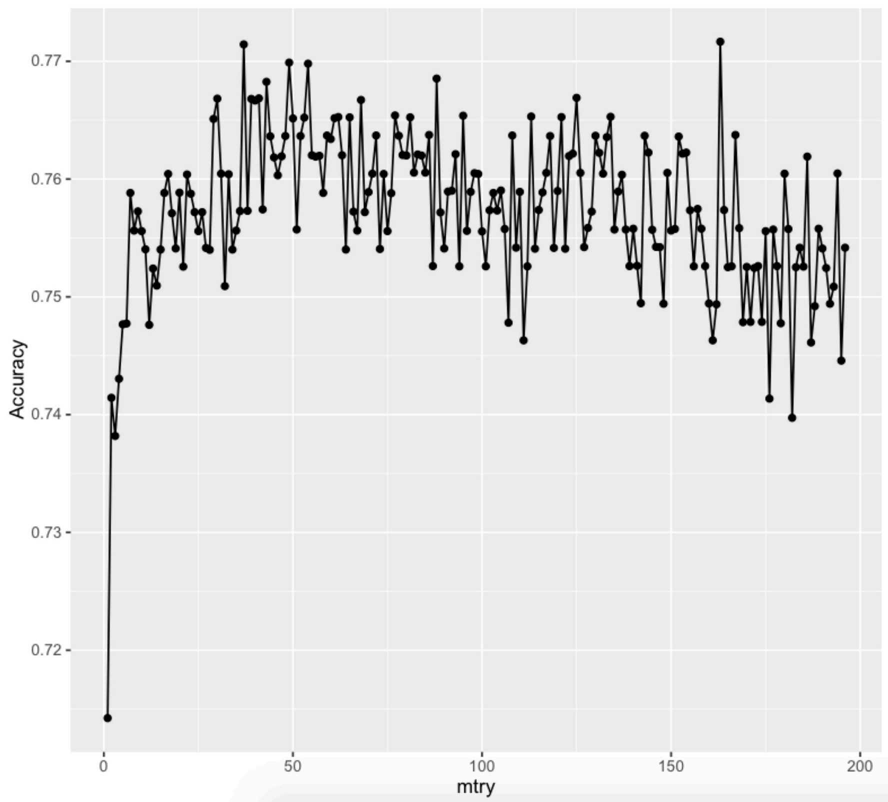


Figure 4.2: Recognition Accuracy vs. *mtry*

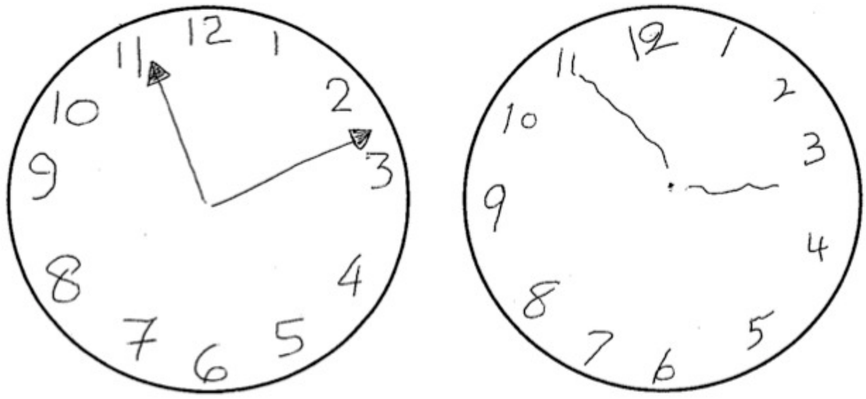


Figure 4.3: Mis-recognitions of dementia image

4.3 Discussion

The obtained results show that the proposed method using SVM could classify 97.1% of the input images into 2 category appropriately. In literature [15], the accuracy for two categories classification, *i.e.* Normal and Dementia, was 89.37%. This value was lower than that of the proposed method. It seems that proposed method has the sufficient performance for practical use. However, the proposed method could not classify some images correctly.

Figure 4.3 shows mis-classification cases of dementia images. In such cases, the size of digits and shapes of the clock hands were quite similar with healthy cases. To recognize them properly, additional information such as pen strokes data will be required.

On the other hand, Random Forest could classify only 53.0% of dementia images correctly. The classification performance was low and not enough for practical use. In this study, the number of images in each type was imbalanced. This made the classification performance drastically decrease. It is one of the reasons. In addition, the features of an input image sometimes quite similar with those of other types. Figures 4.4 and 4.5 show examples of clock drawings given by AD and VaD patients. As you can see, it is difficult to recognize them even for a human because the features of these drawings are quite similar to each other. Moreover, the features of the input drawing are often different from each other even though these dementia types are the same. These show that it is important to classify dementia types based on symptoms.

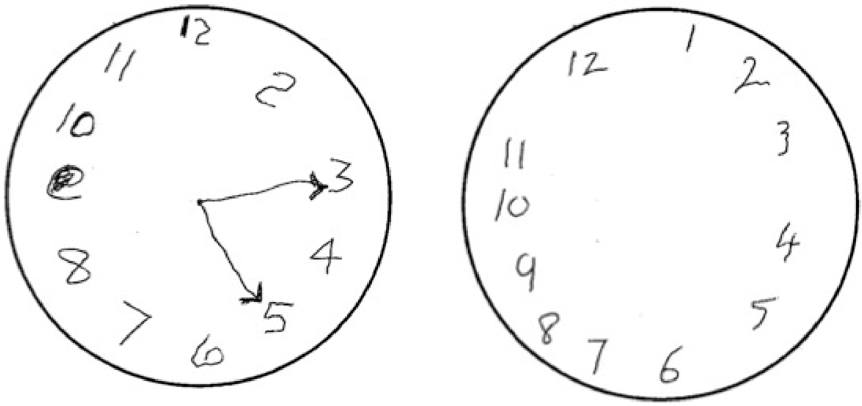


Figure 4.4: Clock Drawings Given by AD Patients

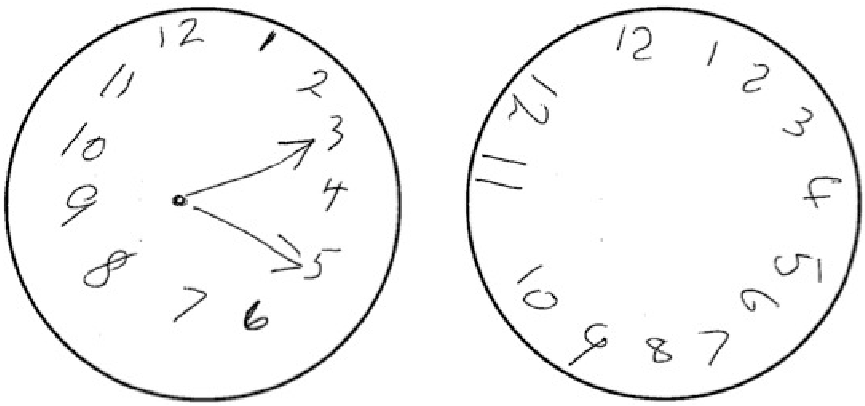


Figure 4.5: Clock Drawings Given by VaD Patients

4.4 Additional Experiment and Discussion — Relationship between Classification Method and its Performance —

In this study, additional experiments using Modifies Bayesian Discriminant Function were conducted. The method is usually used for hand-written character recognition with WDIH. In the experiments, the parameters of MBDF was determined by preliminary experiment, and Leave-one-out Cross Validation method was used to discuss the performance of the proposed method. After this, the accuracies were compared with those of proposed methods.

Table 4.4 shows the summarized experimental results in the cases of two-class (Normal vs. Dementia), and Table 4.5 does the detail of each recognition result in the case of four-class (Normal vs. VaD vs. AD vs. MCI) classification when Nz is 36(6×6). These tables indicate that the classification accuracies were not higher than the proposed method. MBDF does not have sufficient performance for classification. The reason is almost the same described the above. However, MBDF gives a dissimilarity values for classification, *i.e.* the distances from the dictionary. Evaluation of disease progression can be potentially realized by using the obtained dissimilarity values.

Table 4.4: Result of Dementia Detection with MBDF

k	# of Sub-regions (Nz)			
	16(4×4)	25(5×5)	36(6×6)	49(7×7)
15	**87.6%**	87.6%	88.1%	79.5%
16	85.2%	87.6%	88.6%	84.3%
17	85.2%	87.6%	89.5%	84.8%
18	83.3%	**88.1%**	90.0%	86.2%
19	80.5%	**88.1%**	91.4%	87.1%
20	80.0%	**88.1%**	**92.4%**	90.0%
21	77.6%	87.6%	91.4%	**90.5%**
22	76.7%	87.1%	91.4%	90.0%
23	78.1%	87.1%	91.4%	90.0%
24	73.3%	87.1%	91.0%	87.6%
25	73.3%	86.7%	89.5%	89.0%

Table 4.5: Recognition results of each symptom in MBDF

		Recognition Result ($k = 20$)				Total of Images
		Normal	VaD	AD	MCI	
Test Image	Normal	104	0	0	6	110
	VaD	2	15	9	11	37
	AD	5	16	14	20	55
	MCI	3	2	3	0	8

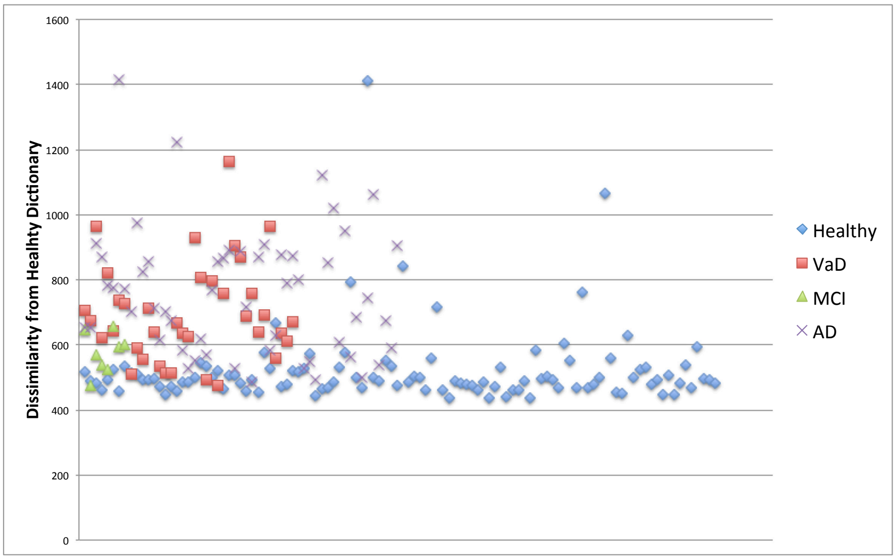


Figure 4.6: Dissimilarity from health images

Figure 4.6 shows the dissimilarity between an input image and the dictionary of healthy drawings. As you can see, the dissimilarities of dementia cases are higher values compared to those of healthy ones. As mentioned in the previous section, the features of the clock drawing given by a dementia patient are usually quite different from those by a health person even though the dementia cases often do not have common features. From these results, it is expected that dementia progression can be estimated by using these data.

Chapter 5

Concluding Remarks

5.1 Conclusion

This thesis aimed to develop a novel method for dementia evaluation, in particular Visuospatial and Executive function, using a drawing test. This study focused on a Clock Drawing Test (CDT), which was one of drawing tests, and discussed a feature extraction method and classifiers for classification of clock drawings. In the proposed method, Weighted Direction Index Histogram (WDIH) method was used to extract features from the drawings, because these images consist of only the clock hands and face. To detect a person's dementia, this study employed Support Vector Machine (SVM), and Random Forest (RF) were used to classify disease types of dementia. The drawing images given by healthy/dementia were collected and these were used in the evaluation experiments.

As a result of the experiments, the proposed method could detect dementia images with an accuracy of 96.8%, and the obtained value was sufficient for practical use in welfare facilities. However, Random Forest could not classify these drawings with high accuracy and classification accuracy was only 53.0%. The classification performance of RF was not good for practical use. On the other hand, this thesis confirmed that the dissimilarity given by Modified Bayesian Discriminant Function (MBDF) will be used for dementia progression analysis.

5.2 Further Works

Random Forest could not classify the given dementia images correctly. If the method is improved and can classify them correctly, we will add not only a clock drawing test but also facial expressions and simple conversations as a comprehensive evaluation.

Our research group is also now collecting and analyzing these data to improve the classification performance of the proposed method. However, plenty of data will be required for progression analysis. More and more images with progression label are required. In addition, more advanced discussions about the relationship between dementia progression and dissimilarity values given by MDBF are also required. These are feature works for this study.

Acknowledgement

First of all, I really would like to express my deepest gratitude to Prof. Shinji Tsuruoka, who is the Executive Vice-President of Mie University, Associate Prof. Haruhiko Takase and Assistant Prof. Hiroharu Kawanaka at Graduate School of Engineering, Mie University who offered continuing supports and constant encouragements.

I would also like to appreciate Prof. Rossi Setchi, Dr. Yulia Hicks and Ms. Zainab Harbi at School of Engineering, Cardiff University, who provided technical helps and science encouragement. In addition, I appreciate Mr. Daisuke Takamatsu and Ms. Kazuyo Ueno at Social Welfare Corp. Taiyo-no-Sato, who provided experimental materials and evaluated the proposed method. In addition, they gave meaningful suggestions and helps to progress this research project.

This research was partially supported by Mie University International Internship Program. Thanks to this program, I could stay in Cardiff University for almost a month for this research project. I would like to thank this scholarship program. And finally, I would like to appreciate other members related my research project.

Reference

[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] 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

[8] 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

[9] 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 Institute of Electronics, Information and Communication Engineers, Vol. J70-D, No. 7, pp. 1390-1397, 1987

[10] 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

[11] 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

[12] Y. Imai, K. Hasegawa,“THE REVISED HASEGAWA’S DEMENTIA SCALE (HDS-R) — EVALUATION OF ITS USEFULNESS AS A SCREENING TEST FOR DEMENTIA”, J.Hong Kong Coll. Psychiair, (1994) 4, SP2, 20-24

[13] Alzheimer’s society, https://www.alzheimers.org.uk/site/scripts/documents.php?categoryID=200362

[14] Folstein MF, Folstein SE, McHugh PR. ”Mini-mental state”: a practical method for grading the cognitive state of patients for the clinician. J Psychiatr Res. 1975;12:189-198.

[15] 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

[16] M. Bennasara, R. Setchi, Y. Hicks, “Cascade Classification for Diagnosing Dementia”, Proc. of the 2014 International Conference on Systems, Man, and Cybernetics, pp. 2535-2540, 2014

[17] Davis R, Libon DJ, Au R, Pitman D, Penney DL. Think, “Inferring cognitive status from subtle behaviours”, the 26th IAAI Conference, 2898-905, 2014

[18] L. Breiman: “Random Forests“, Machine Learning, vol. 45, pp. 5-32, (2001).

[19] K. Takio, ”http://home.hiroshima-u.ac.jp/tkurita/lecture/svm.pdf”, Neuroscience Research Institute, National Institute of Advanced Industrial Science and Technology

Publication List

International Conferences

(1) T. Shigemori, H. Kawanaka, H. Takase, S. Tsuruoka: Development of Dementia Evaluation System Using Conversations and Drawing Tests, Proc. of the 6th International Workshop on Regional Innovation Studies (IWRIS2014)
【Outstanding Paper Award】

(2) T. Shigemori, Z. Harbi, H. Kawanaka, Y. Hicks, R. Setchi, H. Takase, S. Tsuruoka: Feature Extraction Method for Clock Drawing Test, Proc. of the 5th International Symposium for Sustainability by Engineering at Mie Univ. (Research Area C)(IS2EMU2015-C)

(3) T. Shigemori, Z. Harbi, H. Kawanaka, Y. Hicks, R. Setchi, H. Takase, S. Tsuruoka: A study on Dementia Evaluation Method Using Clock Drawing Test, 19th International Conference on KnowledgeBased and Intelligent Information & Engineering Systems (Procedia Computer Science 60, pp.1707-1714, ELSEVIER, 2015)

(4) T. Shigemori, K. Nakamura, H. Kawanaka, H. Takase: A Study on Dementia Evaluation Using Facial Expression Recognition, Proc. of the 7th International Workshop on Regional Innovation Studies (IWRIS 2015)
【Outstanding Paper Award】

(5) T. Shigemori, Z. Harbi, H. Kawanaka, Y. Hicks, R. Setchi, H. Takase: A Study on Scoring Method for Clock Drawing Test, 7th International Conference on Emerging Trends in Engineering & Technology

Domestic Conferences

(1) 重盛友章，川中普晴，高瀬治彦，鶴岡信治，“会話型ロボットによるレクリエーションを利用した認知症評価システムに関する基礎的検討”，第30回ファジシステムシンポジウム

(2) 重盛友章，川中普晴，高瀬治彦，鶴岡信治，“認知症評価システムのための特徴抽出法に関する一検討”，平成26年度電気・電子・情報関係学会東海支部連合大会講演論文集

(3) 重盛友章，川中普晴，高瀬治彦，鶴岡信治，“時計描画テストを用いた認知症評価システム　～タブレット端末を用いたレクリエーションへの活用～”，第４回地域イノベーション学会

(4) 重盛友章，川中普晴，Zainab Harbi，Yulia Hicks，Rossi Setchi，高瀬治彦，“加重方向指数ヒストグラム法を用いた時計描画からの特徴抽出に関する一考察”，第31回ファジシステムシンポジウム

(5) 重盛友章，川中普晴，Zainab Harbi，Rossi Setchi，Yulia Hicks，高瀬治彦，鶴岡信治，“時計描画テストを用いた認知症タイプ分類のための一検討”，平成27年度電気・電子・情報関係学会東海支部連合大会講演論文集
【IEEE Nagoya Section Student Paper Award】

(6) 重盛友章，Zainab Harbi，川中普晴，Yulia Hicks，Rossi Setchi，高瀬治彦，鶴岡信治，“介護施設における職員支援のための取り組みについて”，第５回地域イノベーション学会

(7) 重盛友章，川中普晴，Zainab Harbi，Rossi Setchi，Yulia Hicks，高瀬治彦，“時計描画テストを用いた認知症進行度の推定方法に関する一検討”，三重大学アカデミックフェア 2016