Master's thesis

Automatic Dementia Evaluation System Using Simple Recreation Games and its Development

Kanta Umemura

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

Increasing the number of dementia patients is one of the big social problems in Japan. According to the official report published by the Ministry of Health, Labor, and Welfare, it is expected that 20 % of the elderly will have dementia in 2025, 34.3% by 2060 [1].

Generally, dementia develops due to injury to brain cells, and it makes various functions decrease drastically. According to the literature on dementia researches, there are some sub-types of dementia [2]. The followings are examples of subtypes of dementia.

1. Alzheimer's Disease (AD)
2. Vascular Dementia (VaD)
3. Lewy body Dementia (LD)
4. Frontotemporal Dementia (FD)

In particular, Alzheimer's Disease accounts for 67.6% of dementia in Figure 1.2 [3]. 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 of his/her actions. 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. As a result, people with dementia require various supports based on their symptoms to keep their Quality Of Life (QOL). Generally, The early stages of dementia are called Mild Cognitive Impairment (MCI). 50% of MCI patients progress to dementia within five years. In dementia, a patient's symptom is improved by doing various medication such as training and rehabilitation. Therefore, early detection and prevention of dementia are essential.

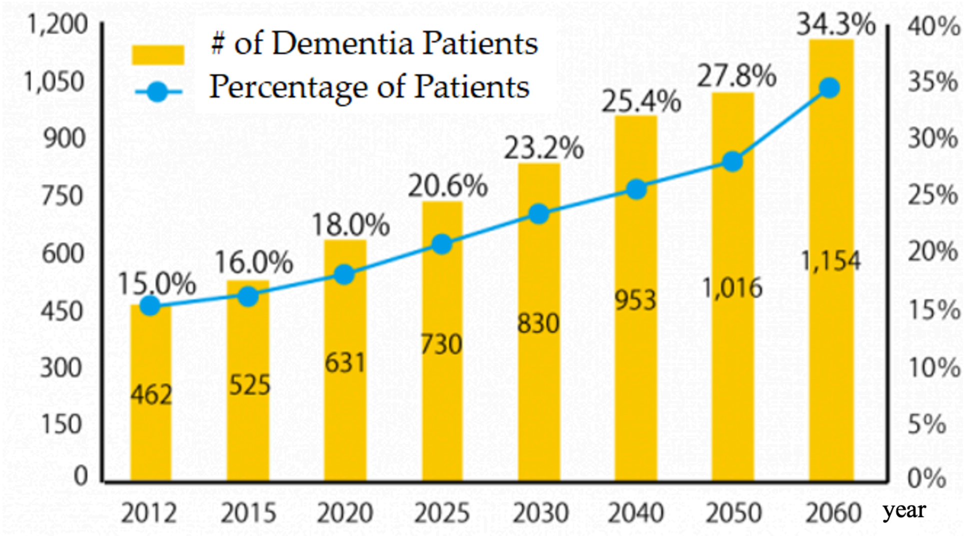


Figure 1.1: Increasing The Number of Dementia Patients

1.2 Dementia Evaluation in Welfare Facilities

Many welfare facilities use dementia check tests, which consist of various tests. Each check test evaluates a cognitive function/orientation of a patient. Therefore, combining plural check tests is important for evaluating a patient's dementia and its type correctly. The check test can evaluate a patient's dementia type and observe its progression as time-series data (aging variation data). Moreover, the obtained results can be used to improve the patient's Quality Of Life. In the field of medical and welfare sciences, it is important to conduct the check test continually. The next subsection explains the check tests used in the evaluation of dementia.

1.2.1 Revised Hasegawa's Dementia Scale (HDS-R)

Revised Hasegawa's Dementia Scale (HDS-R) has been widely used for dementia evaluation in welfare facilities [4]. Generally, this check test consists of 9 simple questions with a maximum score of 30 (Table 1.1). These questions measure some subject's functions, *e.g.*, time orientation, geographical orientation, immediate and recent memories, and so on. In general, if a subject gets a score of less than 20, then the subject has a strong possibility of dementia. If the subject gets a score of 20 points or more is judged to be mild, 11 to 19 points is judged to be middle, and 10 points or less is judged to be severe dementia.

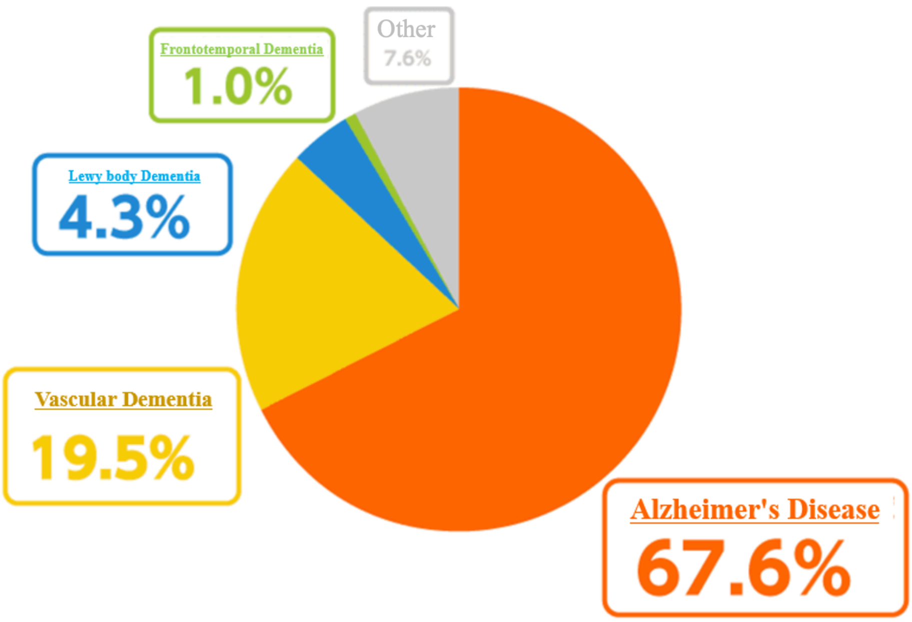


Figure 1.2: Percentage of Dementia Types

1.2.2 Mini Mental State Examination (MMSE)

Mini-Mental State Examination (MMSE) is one of the dementia check tests proposed by Folstein in 1975, which is well known all over the world [5]. This test consists of 11 questions and marks out of 30 based on orientations, calculation ability, memory, language ability, and graphic recognition ability. Table 1.2 shows the detail of MMSE. Almost all of the questions are similar to HDS-R in Table 1.1. MMSE can evaluate the other functions/orientations in addition to those evaluated by HDS-R. For instance, the drawing test (Question 11 in Figure 1.3) can evaluate spatial cognitive function. By using these results, the subject can be classified based on the subject's symptoms. There are some criteria for evaluation, and Table 1.3 shows some of them.

1.3 Problems in Evaluation Methods

These evaluation tests, however, have some problems as follows. First, some elderly persons often become very nervous about the evaluation tests. As a result, the obtained results do not reflect a patient's cognitive functions enough. It means that these tests cannot evaluate accurately. Second, these evaluation tests should be conducted continually to assess a patient's cognitive function because a patient's cognitive function changes depending on the date, place, situation, etc. Therefore, these evaluation tests give much burden to medical staff and care workers [6]. Evaluating content, which is easy and not

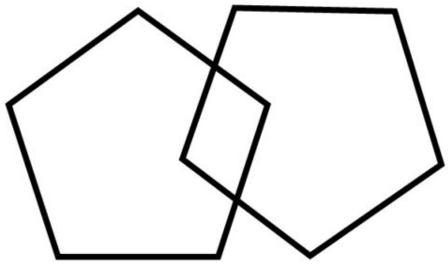


Figure 1.3: Sample Image for 11th Question (MMSE)

stressful, is also required for subjects. If the given contents are difficult and stressful for patients, they are not interested in evaluating contents and will never do them. Finally, time-dependent changes in the progression of dementia in patients cannot be measured, visualized, and analyzed.

1.4 Objective

The final goal of this study is to develop a new system for a quantitative and accurate evaluation of dementia progression. Figure 1.4 shows a rough image of this project. First, this system collects data of patients without his/her awareness and burden. Second, this system measures and diagnosis automatically. If the evaluation result is not good, this system sends the obtained data to medical/facility staff. Therefore, medical/facility staff do not have a burden to diagnose a patient's dementia progression. This study aims to make this system support and help medical/facility staff.

Chapter 2 explains the relationship between hand motion and cognitive function. Also, it explains our developed system focusing on hand motion. Chapter 3 shows experimental materials and some features of hand motion obtained from our developed system. This chapter also shows the details of the experiment, classification using various classification models. Chapter 4 shows the regression analysis using significant features selected in chapter 3. Chapter 5 discusses additional features to increase the accuracy of classification.

Table 1.1: Revised Hasegawa's Dementia Scale (HDS-R)

Question(1) How old are you? （1 point）
Question (2) What is the year? month? 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. (0-5 vegetable (s): 0 point) (6-10 vegetables: 1-5 points)

Table 1.2: 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) (If correct, 1 point)
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.1.3) (All 10 angles must be present and two must intersect. 1 point)

Table 1.3: 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

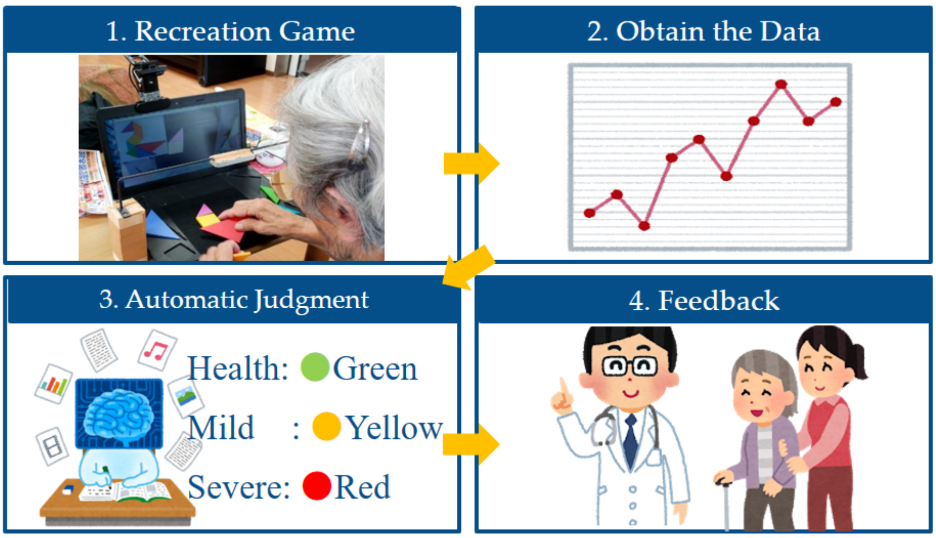


Figure 1.4: Rough Image of Our System

Chapter 2

Developed Recreation Game

2.1 Relationship between Hand Motion and Cognitive Function

There is a lot of literature about the relationship between hand motion and cognitive function. Tachibana evaluated a subject's hand dexterity using the pegboard test [7, 8]. Figure 2.1 shows the image of the pegboard test. The pegboard test can assess hand dexterity measuring how many pins the subject move in time. These reports showed that the relationship between the pegboard test score (hand dexterity) and a subject's cognitive function.

On the other hand, Ito and Yamashita *et al.* discussed the effectiveness of playing a musical instrument and cooking [9, 10]. Their papers showed that these actions were effective in recovering brain function because both hands were usually used while playing musical instruments and cooking. From this point of view, many care houses use exercises using both hands and brain function (in Figure 2.2).

In this paper, the authors focus on hand dexterity and movement of both hands because these factors have some relationship to cognitive functions. Therefore, this study develops a new recreational system to evaluate hand dexterity and activity of both hands to assess a subject's cognitive functions. Also, the authors discuss the relationship between the extracted features and a subject's cognitive functions.

2.2 Simple Recreation Game Using Tangram

The author focuses on the ability to play games. Thus the developed recreational game is shown in Figure 2.3. In the developed system, the authors used a puzzle game like "Tangram". Tangram is a kind of puzzle game that uses triangle and rectangle color pieces. In the game, the user moves the color pieces to make the given figure. The game stage is finished when the user moves the pieces and makes the same figure as the given one. In this study, the author implemented this game into a laptop computer to collect experimental materials. The details of the system are shown in the next subsection.

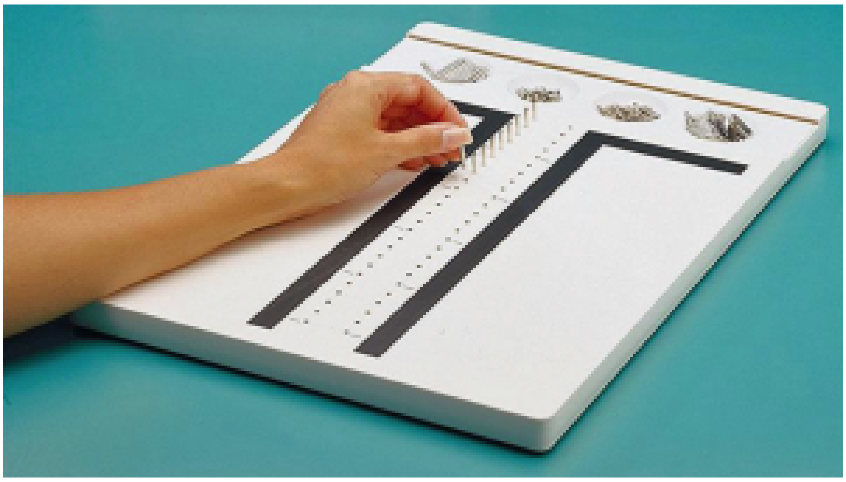


Figure 2.1: Pegboard Test [7]

(a) *Origami*

(b) *Nurie*

(c) Excercize

Figure 2.2: Some Recreation in Care House

2.3 Outline of Developed System

The concept of the developed system is "User Friendly" and "Human-Centered" because it will be mainly used by elderly and dementia patients. The developed system was designed for subjects who did not have much know-how to use a computer. The user only moves color pieces, and then the system automatically recognizes each position of the wood piece and judges whether the game stage is cleared. To realize this architecture, the author employs Leap Motion as a hand sensing device. Leap Motion can recognize a hand in three-dimensional space by using an optical sensor and an infrared camera (Figure.2.4(a)). Leap Motion also has an API for hand tracking/gesture recognition, a system can measure hand motions with the API easily (Figure. 2.4(b)). During the game, the developed system measures the movements of a user's hands in real-time using these functions. Also, this system acquires the coordinates of the user's palm.

Figure 2.3: Developed Recreation Game System in Nursing Home

Figure 2.5(a) shows an example of obtained data by the developed system. In Figure 2.5(a), each column shows coordinates (x, y, z), moving time, and velocity of a user's hand, respectively. The coordinate system used in this system was defined as Figure 2.5(b). This system can measure not only hand motions but also other features at the same time by using the system, and a user's hand motor function can be analyzed and evaluated from the obtained data.

This paper also proposed feature descriptors for the evaluation of hand motor functions and calculated them with the measured data. Table 2.1 shows the list of feature descriptors for this study. These defined descriptors are simple, and they are calculated by simple formulas. For instance, the percentage of moving both hands (P_{mb}) is calculated by

$$P_{mb}(\%) = \frac{t_R \cap t_L}{t_{ans}} \tag{2.1}$$

where t_R, t_L, and t_{ans} mean moving time of a user's right and left hands, answering time, respectively. In the same manner, the percentage of moving dominant hand P_{md}, the percentage of moving non-dominant hand P_{mn}, and the percentage of non-moving both

(a) Overview of Leap Motion

(b) Hand Tracking

Figure 2.4: About Leap Motion

B	C	D	E
−107.897	12.04747	80.35655	6.366
−111.149	−12.8743	78.27509	7.519
88.56513	34.02477	68.31025	8.726
62.20013	−16.1993	67.64905	9.94
69.52234	7.596427	80.64504	11.207
127.9699	54.173	109.5591	12.447
97.89486	14.75408	78.62185	14.829
94.44569	14.55517	73.51907	16.026
117.2021	17.1034	111.9168	17.387

(a) Example of Measured Data

(b) Coordinate System

Figure 2.5: Obtained Data by Developed System

hands P_{nmb} are defined by

$$P_{md}(\%) = \frac{t_R}{t_{ans}}, \tag{2.2}$$

$$P_{mn}(\%) = \frac{t_L}{t_{ans}}, \tag{2.3}$$

$$P_{nmb}(\%) = \frac{\overline{(t_R \cap t_L)}}{t_{ans}}, \tag{2.4}$$

$$t_{ans} = t_R + t_L - t_R \cap t_L + \overline{t_R \cup t_L}. \tag{2.5}$$

With the above formulas, the feature descriptors shown in Table 2.1 can be also calculated. It is expected that these descriptors reflect a user's (patient's) motor functions, *e.g.*, the movement of both hands, hand dexterity, and so on. Also, the author referred to the previous research to calculate features in Table 2.1.

Table 2.1: Features of Hand Motor Function

Number	Feature Descriptor	Unit
(0)	Dominant Hand	Left or Right
(1)	Percentage of Both Hands	%
(2)	Percentage of Dominant Hand	%
(3)	Percentage of No-Dominant Hand	%
(4)	Percentage of Not Moving Both Hands	%
(5)	The Average Speed of Dominant Hand	cm/s
(6)	The Average Speed of No-Dominant Hand	cm/s
(7)	The Maximum Speed of Dominant Hand	cm/s
(8)	The Maximum Speed of No-Dominant Hand	cm/s
(9)	Avg. of X Coordinate of Dominant Hand	
(10)	Avg. of Y Coordinate of Dominant Hand	
(11)	Avg. of Z Coordinate of Dominant Hand	
(12)	Avg. of X Coordinate of No-Dominant Hand	
(13)	Avg. of Y Coordinate of No-Dominant Hand	
(14)	Avg. of Z Coordinate of No-Dominant Hand	
(15)	Standard Deviation of X Coordinate of Dominant Hand	
(16)	Standard Deviation of Y Coordinate of Dominant Hand	
(17)	Standard Deviation of Z Coordinate of Dominant Hand	
(18)	Standard Deviation of X Coordinate of No-Dominant Hand	
(19)	Standard Deviation of Y Coordinate of No-Dominant Hand	
(20)	Standard Deviation of Z Coordinate of No-Dominant Hand	

Chapter 3

Significant Feature for Dementia Evaluation

3.1 Experimental Material

3.1.1 Data Collection

This research project is a collaboration project with Social Welfare Corporation, Taiyo-no-Sato in Matsusaka city, Mie Pref. In the experiment, the author collected the data from 155 subjects, whose age was from 78 to 96 years old. All subjects do not have a problem with hand motor function. Also, the dominant hand of them was the right hand. (The hand that writes letters is the dominant hand) Therefore, this system can't be used for people with restricted hand motor function due to another illness such as stroke.

3.1.2 Labeling for Supervised Learning

This thesis focuses on the relationship between a patient's hand motor function and cognitive function. To analysis the relationship between them, the simple examination on

1. Long-term Memory, and

2. Short-term Memory

were conducted (Table 3.1).

These indexes are usually used to evaluate a patient's cognitive functions. In the examination for long-term memory evaluation, simple questions like "What day is it today?" were used, and long-term memory was ranked from 0 to 3 points. Short-term memory can be evaluated by using how many images the subject can memorize within the given time. In this paper, short-term memory was ranked from 0 to 8; this means the number of memorized images. By using the total scores of the above two simple tests and the advice from an experienced care worker, the collected data were divided into three groups based on a subject's dementia progression, , *i.e.*, Healthy, Mild, Severe progressions (Table 3.2).

Table 3.1: Examination for Cognitive Function Evaluation

Category	Example of Given Questions	Evaluation Criteria and Point(s)
Long-term Memory	What year is it today? What month is it today? What day is it today?	Correct Answer or not 1pt (each question)
Short-term Memory	Do you remeber the [1-8]th given image?	# of Memorized Images (Fig 3.1) 1pt (each image)

Table 3.2: Summary of Subjects (n=155)

Progression Category	Score Range	# of Subjects
Severe Progression	0 to 3 pt	35
Mild Progression	4 to 6 pt	80
Healthy Progression	7 to 11 pt	40

3.2 Supervised Learning Using Multiple Classifiers

This thesis investigated how the proposed feature descriptors work well for dementia evaluation. Therefore, Support Vector Machine (SVM), Random Forest, Naive Bayes, and K-Nearest Neighbors were used with Python 3.7.3, NumPy, and Optuna libraries. The algorithm of these models will be explained in the following session easily.

3.2.1 Support Vector Machine

Support Vector Machine (SVM) is a kind of pattern recognition methods [11]. SVM was expanded to a non-linear discriminant method by combining the kernel learning based on the optimal separating hyperplane. This method is well-known as the best discriminator for 2 categories classification [12]. For classifying of them, the optimal separating hyperplane is determined by the following parameters, σ and C. The classification performance of SVM heavily depends on these parameters. This paper used

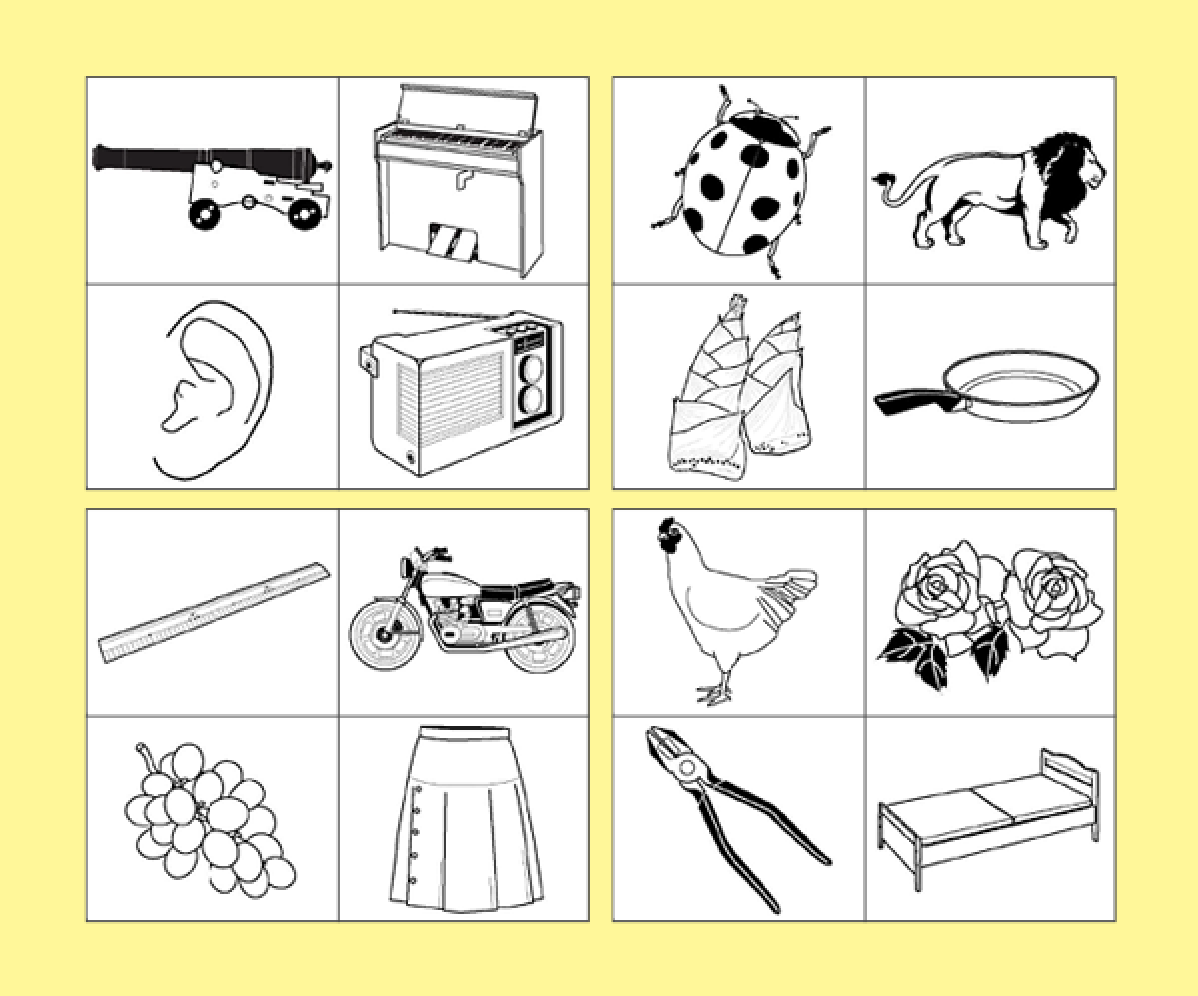


Figure 3.1: Memorized Images to Measure Short-term Memory

Radial Basis Function (RBF) defined by

$$k(x_1, x_2) \quad = \quad -\dot{e}xp\frac{||x_1 - x_2||^2}{2\sigma^2} \tag{3.1}$$

as a kernel of SVM. In the formula, x and σ denotes the data set of each class and the range of infculence of RBF, respectively. These parameters, σ and C, were determined and optimized with a grid search technique.

3.2.2 Random Forest

Random Forest consists of multiple decision trees, and it is a kind of bagging tool [13]. Figure 3.2 shows the rough sketch of Random Forest. First, m sub-dataset is generated using a random sampling method. Next, m decision trees are generated using these data sets. These data are used as training data for the trees. These procedures can generate trees that have a low correlation with each other. Random Forest uses these trees as weak classifiers for classification and outputs the majority vote by a classification result of each tree output.

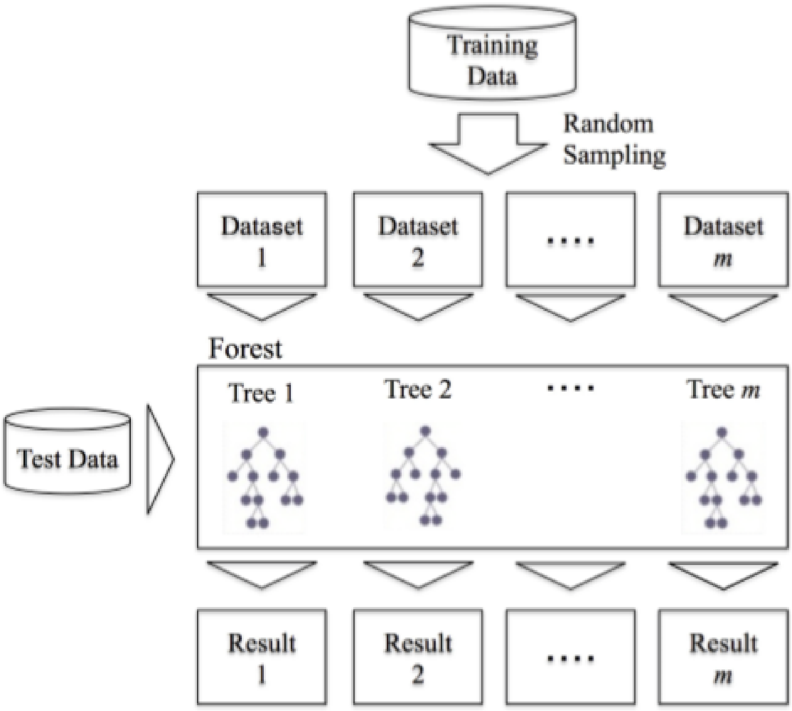


Figure 3.2: Rough Image of Random Forest [13]

3.2.3 K-Nearest Neighbors

K-Nearest Neighbors (K-NN) is a non-parametric machine learning method. This model was developed by Evelyn Fix, and Joseph Hodges in 1951 [14], and later expanded by Thomas Cover [15]. It is used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space.

In the classification, k is a user-defined constant, and an unlabeled vector (a query or test point) is classified by assigning the label which is the most frequent among the k training samples nearest to that query point.

3.2.4 Naive Bays

Naive Bayes is a simple technique for constructing classifiers. For some probability models, Naive Bayes classifiers can be trained very efficiently in a supervised learning setting. In many practical applications, parameter estimation for Naive Bayes models uses the maximum likelihood method; in other words, one can work with the naive Bayes model without accepting Bayesian probability or using any Bayesian methods.

Naive Bayes is that it only requires a small number of training data to estimate the classification parameters. It is an advantage of this algorithm.

3.3 Classification Accuracy of Each Classifier

The author conducted the classification using these classifiers and features of hand motion in Table 2.1. Table 3.3 shows the result of these experiments. In the experiment, SVM showed the highest accuracy, but it was 67.10%. This value was not enough for practical use because the classification accuracy of the conventional approach ,*i.e.*, manual evaluation with HDS-R, was approximately 85% [17]. Also, the cause of the low accuracy is the learning of extra features. Therefore, the author employed feature selection to discuss the importance of the feature.

Table 3.3: Classification Accuracy of Each Classifier (# of Feature = 20)

Classifier	Accuracy
SVM	67.10%
Random Forest	66.45%
K-Nearest Neighbors	56.13%
Naive Bayes	54.19%

3.4 Feature Selection with SVM-RFE

This result indicates that insignificant features were used for learning SVM. As a result, the classification performance had been reduced. Therefore, the author used feature selection to remove the insignificant features.

There are several methods for feature selection, for instance, Forward Selection (FS) and Recursive Feature Elimination (RFE). Generally, RFE requires a large amount of calculation, and the accuracy of classier with selected features is generally higher than other methods [16]. In the experiment, RFE method was used in order to improve classification accuracy.

Table 3.4 shows selected features by SVM-RFE method. They are listed in order of significance. By using this technique, "The Maximum Speed of Hand" or "Avg. of Coordinate of Hand" were regarded as insignificant features and rejected by SVM-RFE.

On the other hand, "Percentage of Moving Both Hand" and "Percentage of Moving Dominant Hand" etc. were selected as important features. The next session shows classification with only significant features selected by SVM-RFE.

Table 3.4: In Order of Significant Features by SVM-RFE (Top 10)

Number	Feature Descriptor	Unit
(1)	Percentage of Both Hands	%
(2)	Percentage of Dominant Hand	%
(3)	Percentage of No-Dominant Hand	%
(4)	Percentage of Not Moving Both Hands	%
(15)	Standard Deviation of Y Coordinate of Dominant Hand	
(6)	The Average Speed of (Dominant, No-Dominant) Hand	cm/s
(20)	Standard Deviation of Z Coordinate of No-Dominant Hand	
(8)	The Maximum Speed of (Dominant, No-Dominant) Hand	cm/s
(19)	Standard Deviation of Y Coordinate of No-Dominant Hand	
(14)	Avg. of (x,y,z) Coordinate of (Dominant, No-Dominant) Hand	

3.5 Classification Accuracy Depends on The Number of Features

As a result of the experiment, the highest classification accuracy was 81.29 %, when the number of features was 3 (Figure3.3). This classification accuracy is enough for practical use because the obtained accuracy is almost the same as a manual approach. Therefore, this result indicates that some feature descriptors about hand motion had a deep relationship with a patient's cognitive functions. However, for advanced discussion, this study needs to discuss how selected features contribute to improving the classification accuracy. SVM-RFE can not calculate the contribution rate. Therefore, this thesis used Random Forest-RFE to calculate them in the next session.

3.6 Feature Selection Using Random Forest

This thesis investigated the importance of feature descriptors using Random Forest and RFE method. Table 3.5 shows the importance score of each feature descriptor. As

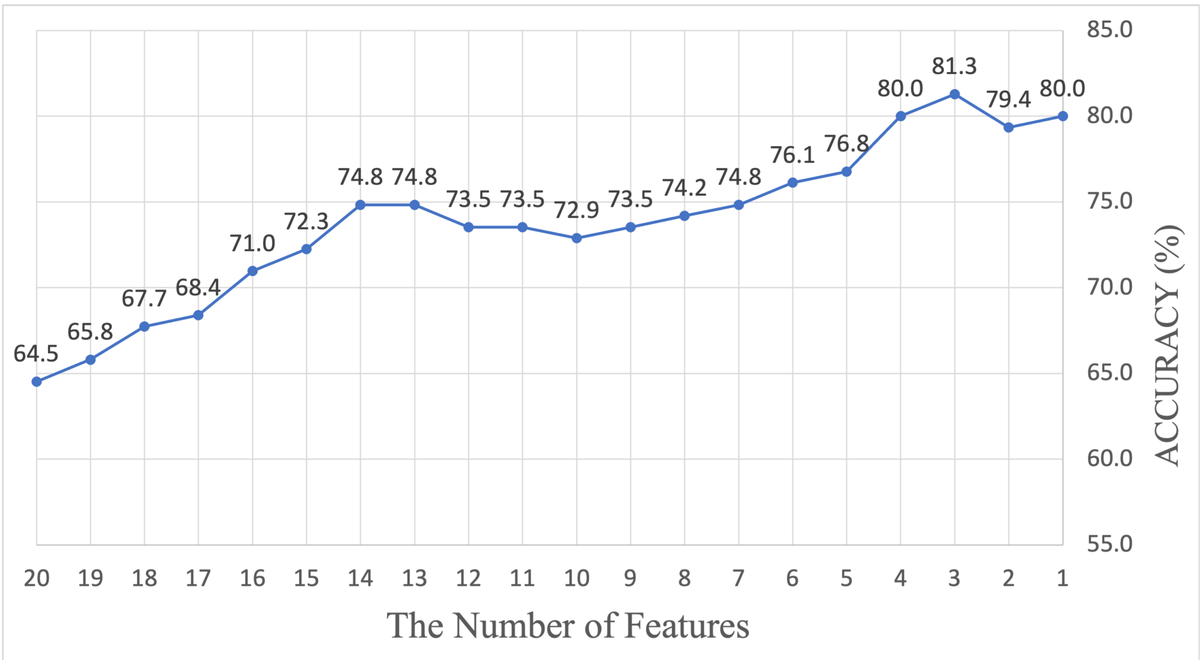


Figure 3.3: Classification's Accuracy depends on the Number of Features

you can see, the top three significant features were the same as the selected features by SVM-RFE, though the classification algorithm was not the same as each other. The obtained results indicate that the selected features were important for dementia evaluation, and they did not depend on the architecture of the classifier.

3.7 Significance of Selected Features

Figure 3.4 shows examples of subjects' hand motion during the Tangram game. Figures 3.4 (a) and (b) show dementia and a healthy person's hand motion, respectively. As you can see, the healthy person used both hands simultaneously during the game; as a result, the value of "Percentage of Moving Both Hands" was increased. On the other hand, the dementia patient could not use both hands but used only the dominant/non-dominant hand. This situation made the value of "Percentage of Moving Both Hands" drastically reduce. This feature will give a great contribution to classification.

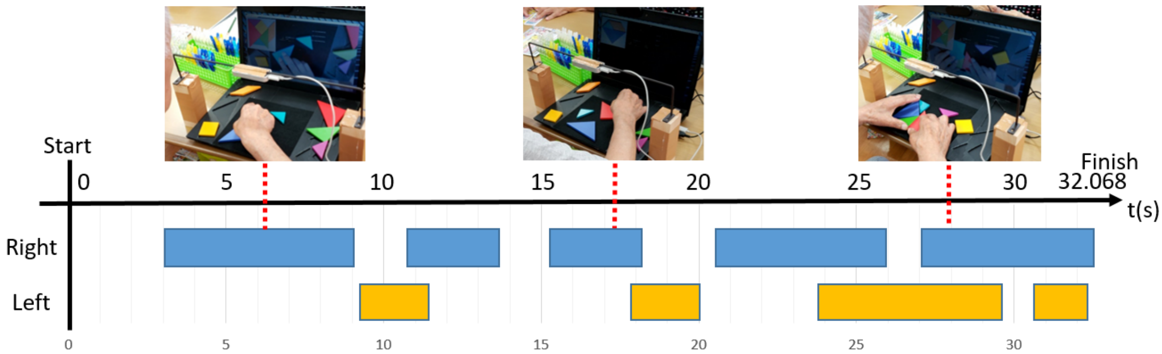
This classification accuracy was improved by using only these three features. SVM classifier hardly recognizes a healthy case as severe (or a severe case as healthy). This result indicates that measuring a patient's hand motion can estimate a patient's cognitive function.

Table 3.5: Importance of Feature by Random Forest-RFE (Top 10)

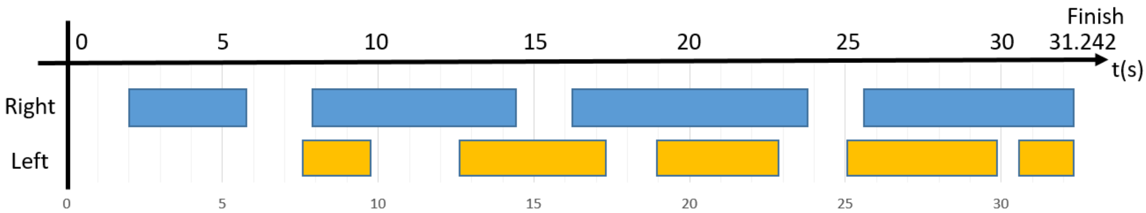
Number	Feature Descriptor	Contribution Rate
(1)	Percentage of Both Hands	0.256
(3)	Percentage of No-Dominant Hand	0.132
(2)	Percentage of Dominant Hand	0.066
(10)	Avg. of Y Coordinate of Dominant Hand	0.044
(4)	Percentage of Not Moving Both Hands	0.041
(20)	Standard Deviation of Z Coordinate of No-Dominant Hand	0.036
(6)	The Average Speed of No-Dominant Hand	0.036
(16)	Standard Deviation of Y Coordinate of Dominant Hand	0.035
(13)	Avg. of Y Coordinate of No-Dominant Hand	0.034
(19)	Standard Deviation of Y Coordinate of No-Dominant Hand	0.033

Table 3.6: Confusion Matrix of Classification

		Prediction Result		
	Dementia Progression	Severe	Mild	Healthy
Actual	Severe Progression	33	2	0
	Mild Progression	4	73	3
	Healthy Progression	2	18	20



(a) Patient



(b) Healthy

Figure 3.4: Examples of Subjects' Hand Motion During Tangram Game

Chapter 4

Investigation of Other Features

4.1 Necessity of Other Features for Dementia Evaluation

In this study, the author developed the system focusing on the relationship between a subject's hand motion and cognitive function. As mentioned in Chapter 3, the result indicated that there was a deep relationship between cognitive function and some features of hand motion. However, the goal of our research project is to introduce our system to care houses. Therefore, the accuracy of this system is not enough so far.

Recent literature focuses on brain function and eye movement to measure a subject's cognitive function [18]. In particular, there were a lot of incorrect patterns like Figure 4.1(b), (c). A kind of factor is related to eye movement or brain function. Therefore, this study needs to look for other features such as eye movement and brain function.

The goal of this paper is to develop a system without the burden of the elderly. Generally, when measuring brain waves, the subject must wear a device on the head. Therefore, a brain-waves measuring device is not suitable.

Also, there are two types of eye-tracking devices. One is worn on the subject's head, and the other is placed at the bottom of the computer's screen. In this experiment, this system uses a stationary type device to reduce the subject's burden.

4.2 Experimental Method

This system used "Tobii Eye Tracker 4C"(Figure 4.2(a)) to track the eye's position. This camera is often used during games such as e-sports (Figure 4.2(b)). Therefore, this device is suitable because the subject doesn't need to wear it. In other words, it is just placed at the bottom of the computer screen. Also, the author decided to use the same recreation game in Chapter 2. The author examined the differences between healthy people and dementia patients when making the presented sample puzzles. Since the beginning of this year, coronavirus infection has made it extremely difficult to collect

(a) Correct Pattern (b) Incorrect Pattern A (c) Incorrect Pattern B

Figure 4.1: Some Pattern of Answer by Dementia Patients

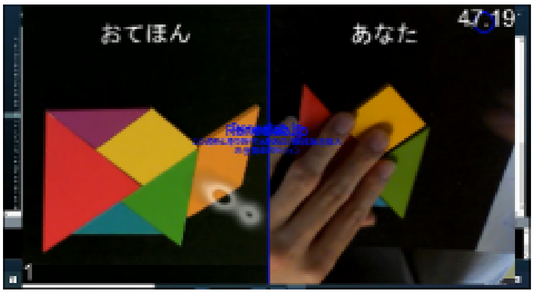
(a) Overview of Tobii Eye Tracker 4C (b) Practical Example

Figure 4.2: About Tobii Eye Tracker 4C

data at care houses. So, the author conducted a preliminary experiment with students in the laboratory.

4.3 Preliminary Experiment by Healthy People

The result of the experiment indicated that a healthy person looks at each piece's positional relationship and make the same figure as the ideal pattern (Figure 4.4(b)). On the other hand, dementia patients can not make the same figure many times shown in Figure 4.1(b), (c). At this stage, this study can not discuss the difference between healthy people and dementia patients. However, the author consider the following reasons why dementia patients cannot make the same figure. It is difficult for dementia patient to memorize and understand positional relationship for a time. In other words as follow,



(a) Detected Observing Point

C	D	E
73.590744	70.91295	7.307
74.55383	62.639755	8.462
−87.30029	82.28048	13.448
−52.11412	91.694214	14.805
4.3005466	104.785	16.036

(b) Measured Data

Figure 4.3: Measurement of Eye Direction

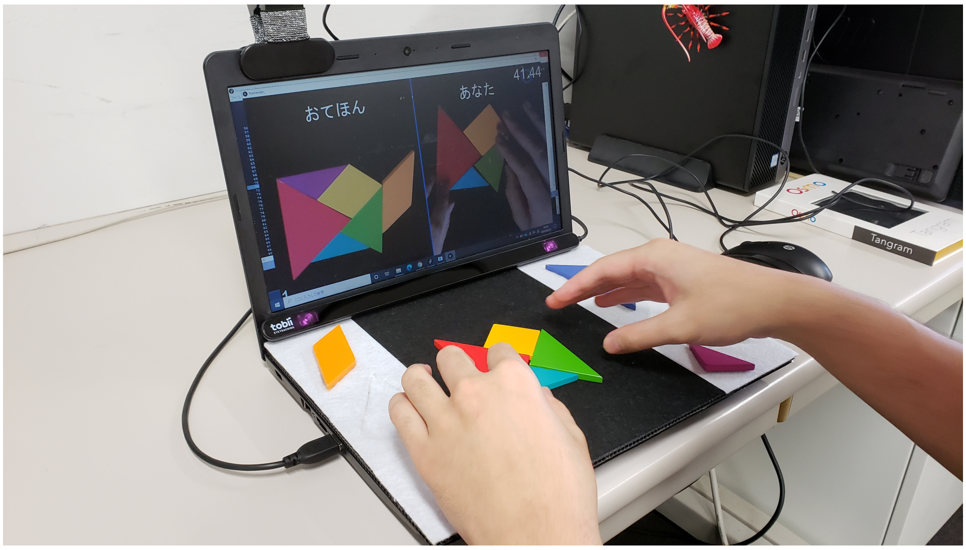


Figure 4.4: Experiment of Eye Movement by Laboratory's Student

1. Deterioration of Short-term Memory

2. Deterioration of Spacious Cognitive Function

In the future, this study has to consider the above discussing points. Therefore, the author plans to conduct same experiments at a care houses using the developed system. Also, this study will discuss whether this system is possible to diagnose the degree of dementia progression.

Chapter 5

Concluding Remarks

5.1 Conclusion

In this paper, the author aimed to develop a new system to reduce the burden of medical staff and elderly persons. The author developed a simple recreation system using Tangram to collect a patient's hand motion and eye movement. As a result of evaluation experiments, some feature descriptors about hand motion had a deep relationship with a patient's cognitive functions, *e.g.*, long/short term memories. By using the obtained features and classifiers like Support Vector Machine, this study could estimate and evaluate a patient's cognitive function. The obtained result looked meaningful, but it was still not enough for practical use.

In the case of dementia, a patient's symptom was improved by early detection and medication. Thus a more advanced and accurate diagnosis system will be required. The developed system is not a diagnosis system, but a kind of recreation system, and it will not give much burden and stress to a patient. There are still many discussing points to develop the ideal system for dementia evaluation. This project will discuss the remained issue to improve the quality of our system.

5.2 Further Works

In the classification using hand motion features, there was a deep relationship between hand motion and cognitive function. However, the current accuracy is not enough to introduce it to care houses. Therefore, it is necessary to find an effective feature in addition to as well as hand motion. Also, the number of data is not enough. Therefore, this study has to continue collecting data and discuss the remaining issues.

Regarding the relationship between eye movement and cognitive function, the author could not conduct experiments on dementia patients because of the COVID-19 issue. So it is necessary to carry them out as soon as the infectious disease is alleviated.

Also, it is necessary to conduct medical care and long-term care online or remotely (without actually facing each other) in the future. Therefore, it is required to develop a new system that can remotely diagnose the degree of dementia progression.

Acknowledgements

First of all, I really would like to express my deepest gratitude to Associate 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 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 to my research project.

Reference

[1] 認知症ねっと, https://info.ninchisho.net/archives/2666

[2] 認知症の種類（アルツハイマー型・レビー小体型・脳血管性・前頭側頭型）, https://www.minnanokaigo.com/guide/dementia/type/

[3] 認知症施策の総合的な推進について, 社会保障審議会介護保険部会（第 78 回）,2020-6-20, 参考資料 2-1

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

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

[6] Hisao Shiizuka, A Survey of Dementia Assessment Scales and Its Related Problems, Research reports of the Kogakuin University, Vol. 111, pp.137 - 144, 2011

[7] Hiro Tachibana, Finger Dexterity and Prefrontal Cortex Activity in Pegboard Performance, Toho Journal, Vol. 47, No. 2, pp.109 - 117, 2018

[8] Son Bo-Young, Effect of task-oriented activities on hand functions, cognitive functions and self-expression of elderly patients with dementia, J Phys Ther Sci., Aug;29(8), pp.1357 - 1362, 2017

[9] Emi Ito, *et al.*, Effect of leisure activities on cognitive functions, Journal of Human Environmental Studies, Vol. 1, pp.15 - 20, 2004

[10] Machiko Yamashita, *et al.*, Measurements of brain activity when cooking using a near infrared measurement device: optical topography system, Toho Journal, Vol. 17, No. 2, pp.125 - 129, 2006

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

[12] Alex J. Smola, Bernhard Scholkopf, “A Tutorial on Support Vector Regression”,Statistics and Computing archive Volume 14 Issue 3, pp. 199-222., 2004

[13] L. Breiman, Random Forests, Machine Learning, vol. 45, pp. 5-32, 2001.

[14] Fix, Evelyn; Hodges, Joseph L. Discriminatory Analysis. Nonparametric Discrimination: Consistency Properties (Report). USAF School of Aviation Medicine, Randolph Field, Texas, 1951.

[15] Altman, Naomi S, “An introduction to kernel and nearest-neighbor nonparametric regression”, The American Statistician, Vol.46 (3), pp175 – 185, 1992.

[16] SVM-RFE: selection and visualization of the most relevant features through nonlinear kernels

[17] Kazuhiro Kohno, Excellent diagnostic tool dementia: The clock drawing test, Biomedical Fuzzy Systems Association, Vo1.6, No.1, pp69 - 79, 2004

[18] Michael D Crutcher, *et al.*, Eye tracking during a visual paired comparison task as a predictor of early dementia, Vol.24(3), pp258-266, 2009.

Publication List

Journal Paper

(1) 梅村勘太, 川中普晴, Yulia Hicks, 手指運動機能の測定を活用した認知症評価システムの開発に関する一試み, 電気学会論文誌 C (電気・情報・システム部門誌), 140 巻 (2020) 12 号, pp.1365-1666, 2020.

International Conferences

(1) Kanta Umemura, Hiroharu Kawanaka, Shinji Tsuruoka, A Measurement of Dementia Evaluation Using Puzzle Game, The 9th International Symposium for Sustainability by Engineering at Mie University (Research Area C), A-11, p23-24, 2019.

(2) Kanta Umemura, Hiroharu Kawanaka, Shinji Tsuruoka, A Measurement of Hand Motor Function for Dementia Evaluation, 第 11 回地域イノベーション学に関する国際ワークショップ (IWRIS2019), No.20, p81-84, 2019.

(3) Kanta Umemura, Hiroharu Kawanaka, Yulia Hicks, Rossi Setchi, Shinji Tsuruoka, Daisuke Takamatsu, A Study on Classification Using Machine Learning for Dementia Evaluation, 2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech 2020), pp101-103, 2020.

(4) Kanta Umemura, Hiroharu Kawanaka, Yulia Hicks, Rossi Setchi, Significant Feature of Hand Motion for Automatic Dementia Evaluation, 24th International Conference on Knowledge-Based and Intelligent Information Engineering Systems, IS36, pp3173-3181, 2020.

(5) Kanta Umemura, Hiroharu Kawanaka, Yulia Hicks, Rossi Setchi, A Study on Important Features for Dementia Evaluation using Simple Recreation, The 10th International Symposium for Sustainability by Engineering at Mie University (Research Area C), A-3, p7-8, 2020.

(6) Kanta Umemura, Hiroharu Kawanaka, Yulia Hicks, Rossi Setchi, Effectiveness of

Hand Motion for Automatic Dementia Evaluation, 第 12 回地域イノベーション学に関する国際ワークショップ (IWRIS2020), No.8, p29-32, 2020.

Domestic Conferences

(1) 梅村勘太, 川中普晴, 鶴岡信治, 認知症進行度評価のための手指運動機能の測定に関する一検討，令和元年度 電気・電子・情報関係学会 東海支部連合大会, K1-3, 2019.

(2) 梅村 勘太, 川中 普晴 , 高松 大輔, 上野 和代, 鶴岡信治, 介護施設における手指の運動機能の計測と認知症の進行度評価に関する一試み, 地域ケアリング Vol.21 No.12, pp54-57, 2019.

(3) 梅村勘太, 川中普晴, 鶴岡信治, 高齢者におけるパズルゲーム中の手の動きと認知機能の関係性に関する一検討，2019 年度 日本生体医工学会東海支部大会，演題 22, p32, 2019.

(4) 梅村勘太, 川中普晴, Yulia Hicks, Rossi Setchi, 上野和代, 高松大輔, 運動機能の評価システムの開発に向けた一検討，第 9 回地域イノベーション学会大会ポスター発表, 演題 8, 2019.

(5) 梅村勘太, 川中普晴, 上野和代, 高松大輔, 高齢者のパズルゲームにおける視線と認知機能の関係に関する一考察, 令和二年度 電気・電子・情報関係学会 東海支部連合大会, H6-5, 2020.

(6) 梅村勘太, 川中普晴, 上野和代, 高松大輔, レクリエーションゲームを活用した認知機能評価システムの開発に関する一試み, 2020 年度 日本生体医工学会東海支部大会, B1-17, 2020.