Statistical Analysis of Micro-error Occurrence Probability for the Fitts' Law-Based Pointing Task

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Abstract. Identifying mild cognitive impairment (MCI) at an early stage and preventing its progression to dementia has become an important task. In order to solve this problem, we focused on micro-errors (MEs), including stagnation of behavior, as a criterion for discriminating between healthy subjects and MCI patients. According to the naturalistic action test (NAT), when the difficulty of the task (index of difficulty: ID) is increased, the occurrence frequency increases drastically. In this research, we aimed to develop a model that simplifies the virtual kitchen challenge (VKC), which reproduces the NAT task on a tablet terminal, and estimates the ME occurrence probability based on a learning difficulty model that considers shape similarity. In this study, 20 university students were asked to perform a shape task. Using the generalized linear model showing the relationship between the occurrence probability of the ME and the result of the shape task, we confirmed that the ME occurrence probability increases with the difficulty level. Moreover, as future work, it is necessary to investigate the influence of handedness and gaze and the relation between color similarity and planning with regard to the ME occurrence probability.

Keywords: Mild cognitive impairment · Micro-error · Instrumental activities of daily living

1 Introduction

It is important to identify mild cognitive impairment (MCI) in older adults at an early stage to prevent progression to dementia. As of 2018, it is estimated that the number of people suffering from dementia worldwide will increase from 50 million to 82 million by 2030 and to 152 million by 2050 [1]. It is estimated that in Japan itself, the number of people with dementia will increase to about 4.62 million in 2012 and 6.75 million in 2025 [2]. The prevalence and the disease rate of dementia markedly increases with age,

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and 40–60% of dementia is reported to be Alzheimer's disease. Neither the cause of the disease nor the treatment has been clarified; the only measure taken is to delay the progression. Therefore, it is necessary to detect the precursor stage of dementia early and to prevent the onset of dementia. Of individuals diagnosed with MCI, which is the precursor stage of dementia, up to 50% may meet the criteria for dementia within 5 years [3].

Currently, cognitive function tests such as Mini Mental State Examination (MMSE), Revised Hasegawa Type Simple Intelligence Assessment Scale (HDR-S), and Clinical Dementia Rating are widely used for screening dementia [4]. These tests are face-to-face tests intended to evaluate the subject's memory, awareness, executive function, etc. For the MMSE, though the discrimination accuracy at the severe disability stage is about 100% at the stage of moderate dementia and about 50% at the stage of mild dementia, the discrimination accuracy at the MCI stage is only about 30%. Thus, the low accuracy is a challenge. Therefore, it is necessary to develop a new screening method with higher identification accuracy.

In a previous study, an index called micro-error (ME) that models the stagnation of motion during the reaching operation has been used to describe the behavioral characteristics of MCI patients. In recent years, it has become clear that there is a significant difference between healthy subjects and MCI patients in terms of the ME occurrence frequency, and an approach to discriminate MCIs based on the occurrence frequency of MEs gained attention. MEs have a characteristic that the occurrence frequency drastically increases when the average difficulty of a subtask, which is a detailed operation constituting an IADL task, is increased [5]. The nature of IADL tasks can be simplified as reaching and selection tasks. In addition, the performance in these tasks may be influenced by information such as the shape and color of objects to be selected, their implications or functions, and the planning needed to complete the task. However, it is not clear what kind of information strongly influences the occurrence of ME.

The overarching goal of this work was to develop a model to estimate the probability of ME occurrence in everyday tasks. The aims of this study were to (1) examine the influence of reaching difficulty and distractor similarity to the target on ME and (2) determine whether the MEs can be rapidly quantified as the difference between the direct path to the target and the actual reaching path to the target, with the ME expected to generate differences greater than the accurate reaching movements.

1.1 Virtual Kitchen Challenge (VKC) System

In a previous research, we developed the Virtual Kitchen Challenge (VKC) system, which measures the performance in a VR-IADL on a tablet touch screen. The VKC was modeled after the Naturalistic Action Test (NAT), a performance-based test of everyday functions that requires participants to complete tasks using real objects that are presented on a table. The VKC addresses numerous methodological challenges associated with the NAT, including the time required for set-up and scoring. In the VKC task, actions are mapped to interactions such as touching and dragging the screen of the tablet. The Lunchbox Task consists of four main tasks: (1) make a peanut butter and jelly sandwich; (2) select and wrap cookies; (3) fill a thermos with juice; and (4) pack and close the lunchbox. Distractor objects that are not necessary for the task also are included in the task environment. Figure 1 shows the Lunchbox Task in a VKC system. Past work has shown significant correlations between the ME observed during completion of the VKC and that observed during the completion of the NAT [5].

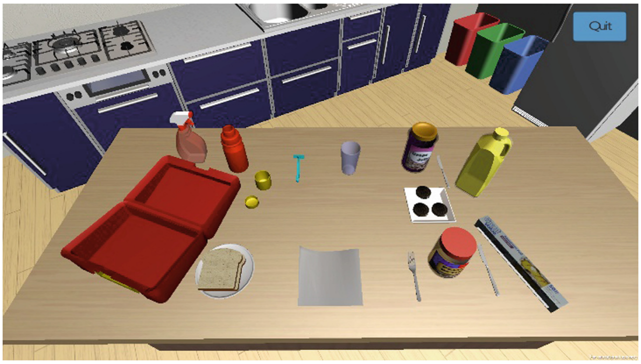

Fig. 1. VKC system.

1.2 Shape Task

The VKC is a complex, self-paced task during which the participant may sequence the task in a number of ways. To impose greater control on responses during object selection, we developed the shape task. The shape task divides each object selection into an independent trial. Trial completion time includes the time required to identify and select the target object from among an array of distractor objects and the time required to move the hand to the target object. These two aspects of each trial were modeled according to Fitts' law and Hick's law [6].

In the VKC, individuals make more ME during more difficult tasks and when there are distractor objects that are similar to the target object. Thus, we investigated the influence of trial difficulty and distractor-target similarity on ME occurrence by means of the shape task.

1.2.a. Trial Difficulty - Trial difficulty was quantified based on Fitts' law, which provides a model of human motion in the man–machine interface. Fitts modeled the relation of speed and accuracy tradeoff with the target movement. The model equation is shown in Eq. (1). Here, D is the distance to the target object; W is the size of the target object; and MT is the movement time. In addition, "a" indicates the start time or stop time of finger movement, and "b" indicates finger speed. In addition, Eq. (2) presents the index of difficulty (ID). The ID quantifies the difficulty at the time of task execution.

$$MT = a + b\,log_2\left(\frac{D}{W} + 1\right) \quad (1)$$

$$ID = log_2\left(\frac{D}{W} + 1\right) \tag{2}$$

We expect that in the shape task, ME will increase with ID. Specifically, in the shape task, the ID increases as the distance from the start point to the target object increases; we expect more ME in trials in which the target object is farther from the start point.

1.2.b. Target-Distractor Similarity - Target-distractor similarity was quantified using the correlation coefficients between the shape of each of the nine distractor objects (DO) and the target object (TO). The correspondence between each object and the correlation coefficient is shown in Fig. 2 and Table 1.

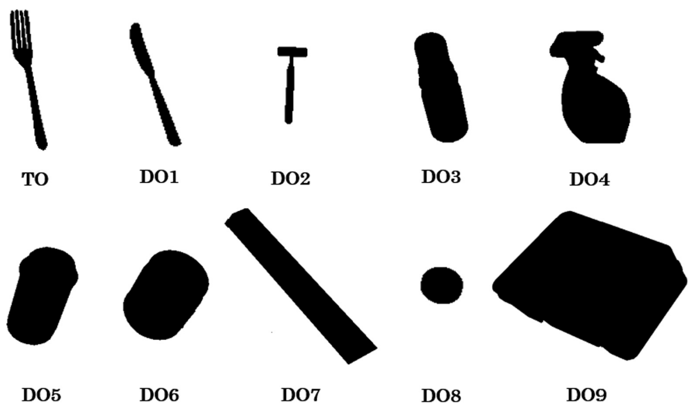

Fig. 2. Target object (TO) and nine distractor objects shown in order from the most similar to the least similar.

Table 1. Shape similarity

DO	Similarity
DO1	0.8052
DO2	0.4755
DO3	0.4328
DO4	0.4099
DO5	0.3799
DO6	0.3223
DO7	0.2976
DO8	0.2465
DO9	0.0901

Questionnaires were administered to validate the objective assessment of target-distractor similarity against subjective perceptions. The contents of the experiment show the objects in the two circles displayed slightly above the red dot and the red dot at the same time (Fig. 3). At that time, the user was asked to evaluate how much the object displayed in the second circle could be distinguished in 5 stages. Further, we evaluated all DOs based on the subjective time length difference required to discriminate. From the results of this preliminary experiment, the coefficient of determination ($R^2 = 0.5736$) and the correlation coefficient ($r = 0.759$) were obtained. We found that there exists a strong positive correlation between the similarity of the subjective form and the similarity degree of the form quantitatively calculated. The results are shown in Fig. 4.

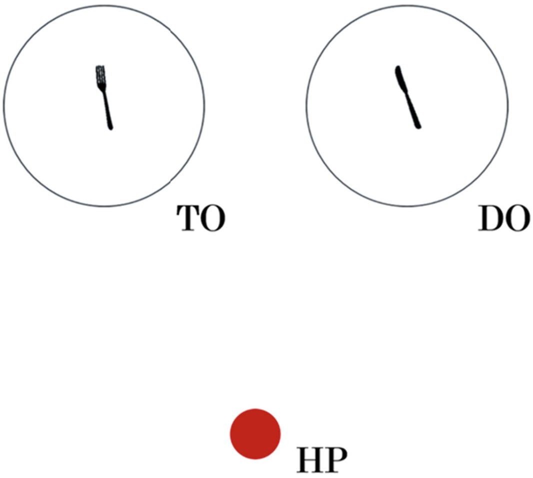

Fig. 3. Screen during the questionnaire experiment. (Color figure online)

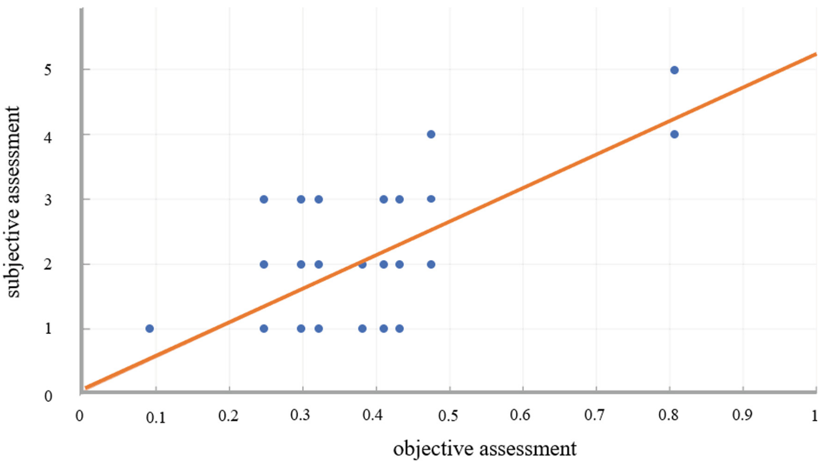

Fig. 4. Relationship between subjective assessment and objective assessment.

1.2.c. Shape Task - Twenty university students were recruited to perform the shape task. In this task, participants had to rest the index finger of their right hand on a central red start button and then reach to the fork (TO) as quickly and accurately as possible in each trial. In all, 200 trials were conducted with 10 stimulus arrays with different task IDs presented 20 times in a random order. The task screen is shown in Fig. 5.

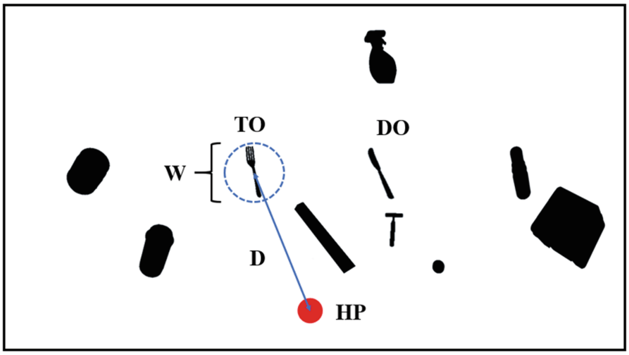

Fig. 5. Task screen (Color figure online)

Participants were video-recorded as they performed the task. Video recordings were used to code the MEs. The MEs included perturbations of reaching movements that were observable by trained human coders. Coders recorded the time when the ME occurred, the type of the ME (mis-reach or touching of a distractor object). The distractor objects that were touched were recorded. However, most ME were reaching errors where the intended object was not clear. For mis-reaching errors, the direction of the reaching error was recorded as left, right, or center.

2 Results

2.1 Validation of the Index of Difficulty – Completion Time × ID

When studying the relationship between completion time and ID, we examined the subject's response time (seconds) and standard deviation (SD). The results are listed in Table 2.

Table 2. Average speed of subjects

Subject	Average speed	SD
1	1.1237	0.2020
2	1.2440	0.2256
3	1.0861	0.1949
4	1.1679	0.1767

(*continued*)

Table 2. (*continued*)

Subject	Average speed	SD
5	1.4837	0.2354
6	1.1854	0.1661
7	1.0913	0.1468
8	1.2514	0.1264
9	1.1302	0.1808
10	1.1495	0.1379
11	1.4149	0.1451
12	1.1294	0.1497
13	1.4233	0.1848
14	1.3145	0.1203
15	1.1026	0.1544
16	1.2894	0.1787
17	1.7398	0.2146
18	1.1072	0.2083

A regression analysis was conducted to investigate whether the item difficulty in the shape task could be explained by Fitts' model. The results of the regression analysis of Subject 1 and the results of the determination coefficients (R^2) and correlation coefficients (r) of all subjects are presented in Fig. 6 and Table 3, respectively. The data of two examinees are excluded as outliers.

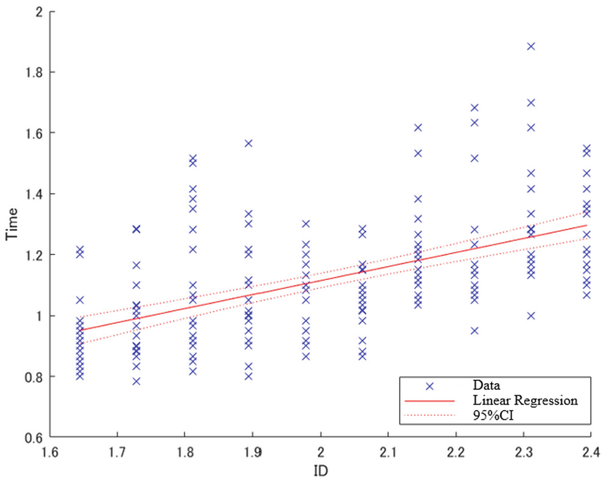

Fig. 6. Results for Subject 1.

Table 3. Coefficient of determination and correlation coefficient

Subject	R^2	r
1	0.2934	0.5417
2	0.3159	0.5620
3	0.0745	0.2729
4	0.1442	0.3797
5	0.2096	0.4578
6	0.0734	0.2709
7	0.2367	0.4865
8	0.4621	0.6798
9	0.2442	0.4942
10	0.2047	0.4524
11	0.1464	0.3826
12	0.2014	0.4488
13	0.3811	0.6173
14	0.4100	0.6403
15	0.3429	0.5856
16	0.3835	0.6193
17	0.3492	0.5909
18	0.1706	0.4130

From the data in Table 3, weak to moderate positive correlation was obtained for each subject. Thus, it is confirmed that the required time increases with the ID.

2.2 ME in the Shape Task

The mean value and SD of ME in the shape task (Mean = 48.0556 SD = 30. 6077). The relationship between speed and accuracy was also investigated, but the number of ME occurrences differed depending on the subject even if the average speed was close.

2.3 Relation Between ME and Item Difficulty (ID)

The relation of the ME occurrence probability with the ID of each subtask was modeled by the generalized linear model. Figure 7 shows the diagram modeling ID as an explanatory variable and ME occurrence probability as the objective variable in the model. Table 4 lists the estimated values of the coefficients.

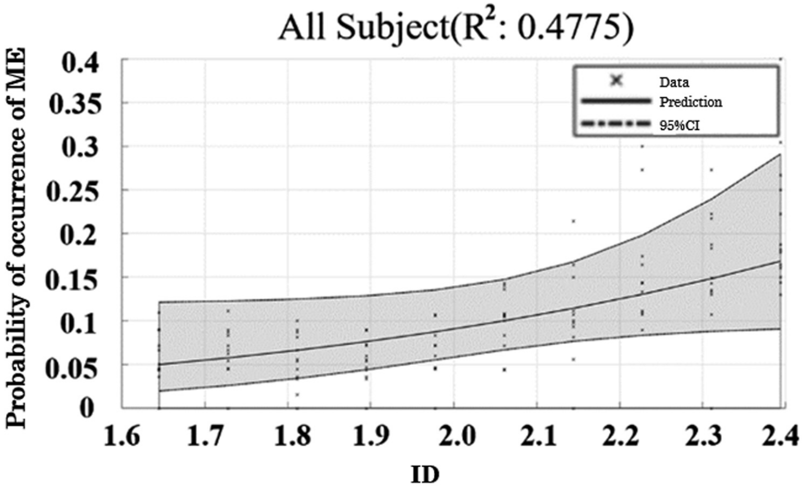

Fig. 7. Probability of occurrence of ME for ID.

Table 4. Estimated coefficients.

			95%CI			
	Estimate	STD error	Lower limit	Upper limit	t-value	p-value
Intercept	−5.8972	2.0406	−9.9181	−1.8763	−2.8899	0.0039
ID	1.7962	0.9664	−0.1080	3.7005	1.8587	0.0631

The coefficient of determination was 0.4775 (correlation coefficient: 0.6910). This result suggested that the probability of ME occurrence increased with increasing difficulty level.

2.4 Relation Between ME and Target-Distractor Similarity (DO)

Figure 8 shows the ME generation probability for each DO that was coded as the target of ME generation.

2.5 Relation Between ME Target Similarity and Reaching Difficulty (ID)

The hypothesis that ME would be likely to occur in the case of highly similar objects when the ID is especially high was evaluated by examining the occurrence of ME in trials where DO1 (i.e., the distractor most similar to the target) was on the right or left side of the target across trials that differed in terms of the reaching difficulty (ID). Figure 9 shows the probability of ME occurrence with respect to ID based on TO. Then, an analysis of variance (ANOVA; Table 5) was carried out considering the effect of ID and direction and its interaction.

The results of the ANOVA showed that the directional effect was significant ($F(1,17) = 20.31$, $p < .001$), and the interaction too was significant ($F(9,153) = 3.583$, $p < .001$).

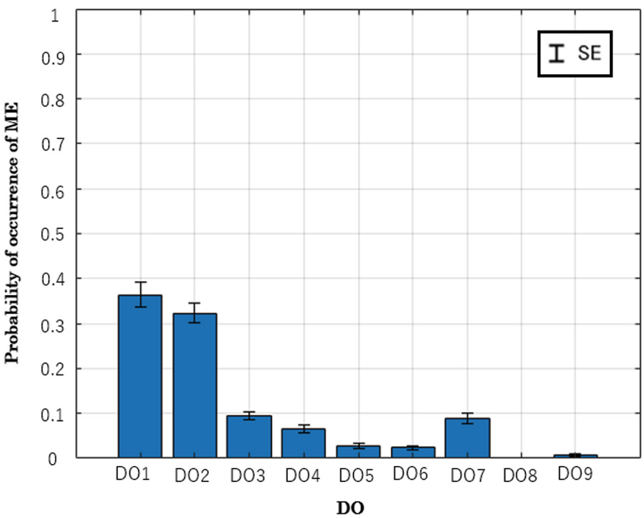

Fig. 8. Probability of occurrence of ME for DO.

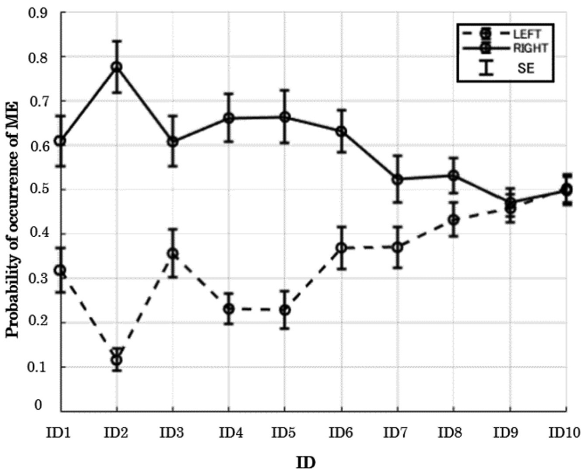

Fig. 9. Average plot of ME occurrence probability for ID.

Table 5. Result of analysis of variance

	SS	df	MS	F-value	p-value	
ID	0.3777778	9	0.04198	1.332	0.2248	
Direction	6.2020171	1	6.20202	20.31	0.0003	****
ID × Direction	3.6744323	9	0.40827	3.583	0.0005	****

+ p < .10, * p < .05, ** p < .01, *** p < .005, **** p < .001
*: significant

2.6 Relationship Between the Most Direct Path to the Target and the ME Path

Figure 10 shows a part of the figure in which the trajectory of the index finger in each trial in the shape task for Subject 1 is compared with the most direct path from the start point to the target. The difference between those paths is quantified (indicated by the area). Trials in which an ME was coded are represented by an orange background. A Support Vector Machine was applied using the area of the trajectory of each trial as learning data. The ROC curve is shown in Fig. 11.

The precision is 80.6%, and the AUC is 0.67, which is not as high as the predicted performance.

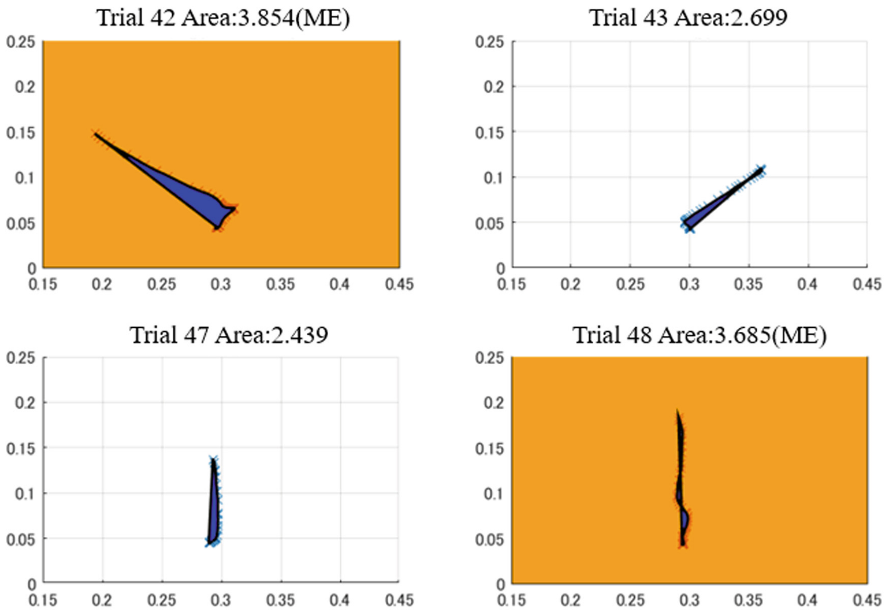

Fig. 10. Relationship between the track area and ME. (Color figure online)

3 Discussion

3.1 Consideration of the Influence of Reaching Difficulty and Distractor Similarity to the Target on ME

Using the generalized linear model, we confirmed that the ME occurrence probability increases with ID. Therefore, it is suggested that the ME occurrence probability can be quantitatively estimated from the ID. Moreover, examination of the relationship between ME and DO shows that many MEs occur in objects with high DO similarity. ME occurs when the similarity of DO is high, and this is observed equally at all IDs.

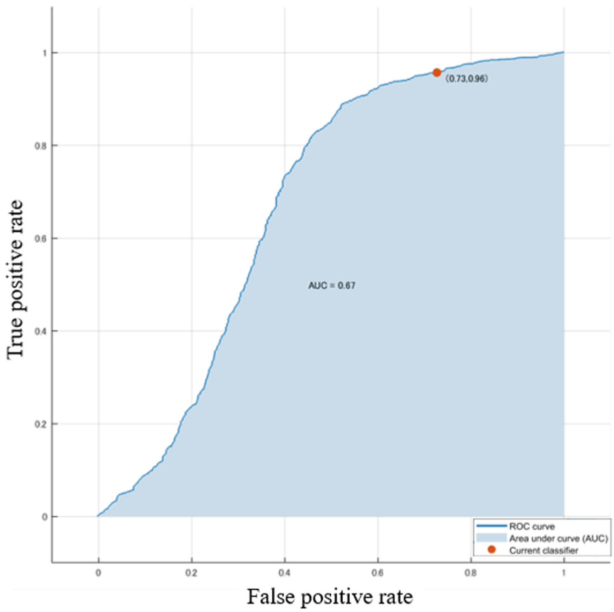

Fig. 11. ROC curve.

Furthermore, since the same tendency was seen when the position of DO was randomized, generation of ME is considered to be greatly influenced by the shape.

In this study, although the generalized linear model was applied, since there are individual differences between subjects, We will be modeled using the generalized linear mixed model and the hierarchical Bayesian model to create a more appropriate model.

3.2 Consideration of the Ease of Occurrence of ME Due to Left/Right Side Differences

If the ID is low, there are clear differences in the ME occurrence rate between the left and right sides. However, as the ID increases, the difference gradually disappears. From the results of ANOVA, significant differences were found in the factors of presenting direction of DO1 to TO; however, the interaction was also significant. The following explanations can be given: The subject's dominant hand and the fact that the task in this experiment was controlled to be performed by the right arm.

3.3 Relationship Between the Track Area and ME

The accuracy of the ROC curve is 80.6%, and the AUC is 0.67, which is not so high as the predicted performance. However, we think that it is possible to automatically discover the ME depending on the improvement. Conventionally, it is thought that coding of ME is judged by viewing the video during the task, but if we can judge the

ME from the area of the locus with high accuracy, the value can be used for early detection of MCI in a short time.

4 Conclusion

It is suggested that the degree of difficulty can be quantified by the relationship between the difficulty level on a subtask basis and the occurrence frequency of ME. This suggests that the probability of ME occurrence can be estimated from the ID value. As a future work, we will conduct comparative analysis not only for young people, but also for healthy elderly and MCI patients. Regarding the measured data, we will model not only generalized linear models, but also generalized linear mixed models considering individual differences and hierarchical Bayesian models with higher degrees of freedom. Further, the results of this experiment showed that the direction of ME was significant when TO was used as a reference. In order to investigate the cause, it is necessary to investigate relationships of gaze behaviors and dominant hands during tasks. Furthermore, in order to investigate the relationship between ME and area, investigate the relationship between area and ID, and the similarity of DO. Although this research focused on the investigation of the influence of the form, in the future, we will also investigate the relationship between color similarity and planning and the occurrence probability of ME.

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