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Quantifying Finger-tapping-test Scores using a Three-dimensional Motion Analysis Program: A Preliminary Study

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The symptoms of Parkinson's disease are evaluated through the Finger Tapping Test (FTT), but this method has some limitations. Therefore, we evaluated the clinical applicability of motion software based on artificial intelligence (AI) technology developed by our research team. FTT videos of five young participants and eight elderly participants were analyzed through the AI-based software. As a result, when the fingers were spread out and folded, statistical differences were estimated in the 'distance' between the thumb tip and the index fingertip (p = 0.032, 0.008, respectively). Also, when the fingers were spread out, a statistical difference was found in the angle (p = 0.008). These preliminary research results showed the possibility of developing an FTT evaluation technique based on AI software in the future. The results of this study are expected to be helpful in the development of quantitative evaluation tools for neuro-rehabilitation with electromagnetic brain stimulation.

Keywords : deep learning, quantitative assessment, finger tapping test, 3D Motion, electro-magnetic stimulation

1. Introduction

The world is moving from an aging society into a super-aging one. Two thousand eighteen was the first year in which the number of people aged 65 exceeded the number of children under 5. As the population grows, health care for the elderly has become an important issue [1], and the number of patients with cranial nerve diseases, including epilepsy, dementia, Parkinson's disease, and stroke, has sharply increased. Among them, Parkinson's disease is one of the most common diseases in the elderly, and the incidence rate is steadily increasing [2]. Parkinson’s disease is a neurodegenerative disease caused by a decrease in dopamine secretion due to the death of dopaminergic neurons in the substantia nigra [3]. The motor symptoms of Parkinson's patients include tremors, rigidity, bradykinesia, and postural instability [4]. Bradykinesia is the most common symptom in Parkinson's patients [5]. As Parkinson’s disease progresses, the symptoms of bradykinesia worsen, making it difficult to perform daily activities [6]. Therefore, it is important to evaluate bradykinesia among the clinical features of Parkinson’s disease [7].

As a clinical test for diagnosing the symptoms of Parkinson’s disease, the unified Parkinson’s disease rating scale (UPDRS) is mainly used. This scale is a method of evaluating four domains: 1) mentation, behavior, and mood; 2) activities of daily living (ADL); 3) motor examination; and 4) motor complications [8]. The Finger Tapping Test (FTT) is included in the motor examination test items of the UDPRS and is a neurophysiological examination that assesses upper extremity bradykinesia. The FTT is a test in which the patient is asked to tap their fingers for 10 to 15 seconds as quickly and widely as possible. In the FTT scoring method, the occupational therapist evaluates the speed, amplitude, and hesitancy as the subject taps their fingers [9]. The FTT is scored as 0 (normal), 1 (slight impairment), 2 (mild impairment), 3 (moderate impairment), or 4 (severe impairment) through

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the observations of the examiner [10]. Slowing speed, loss of amplitude, and hesitancy in finger tapping indicate the presence of bradykinesia, one of the most important symptoms of Parkinson's disease [11]. However, the FTT scoring method may not be reliable due to its subjective nature since it depends on the experience of the examiner leading to significant differences between the measured values [12]. In addition, the FTT scoring system has limitations in evaluating the clinical characteristics of bradykinesia [13].

Additionally, since there is no quantification of the movement results, it is difficult to grasp the progression of the symptoms quantitatively. Repeated testing may reduce the reproducibility of the diagnosis [13]. Positron emission tomography (PET) and single photon emission computed tomography (SPECT) are used for the diagnosis of Parkinson's disease [14]. Although, in the case of SPECT, the protocol is too long and inefficient. In contrast, PET has improved image quality, higher diagnostic accuracy, and the advantage of providing a short protocol; however, it has the disadvantage of high radiation exposure and medical cost [15]. Recently, wearable sensors were developed as a solution to these limitations in diagnosing Parkinson's disease; [16, 17] however, data overload is a big disadvantage. The vast amount of information can impose a higher workload on the occupational therapist, and wearable devices are patient-driven, not clinician-driven [18]. Since wearable devices are patient-driven, the information can change with the patient's condition, and if a patient feels discomfort while wearing the device, data may be contaminated.

Therefore, several techniques have been studied to calculate the FTT quantitatively to solve these disadvantages. A vision-based motion recognition model has been presented to evaluate the FTT quantitatively. The Markov chain fusion model was used in this study, and a spatial-temporal mechanism was developed [19]. A gyro sensor was used for the quantification of the FTT. All the indicators of the sensor showed a significant difference between the control group and the Parkinson's disease group, and the correlation with FTT was confirmed [20]. A computer vision framework was proposed to evaluate the FTT. The video recordings of the FTT and the developed model could classify the Parkinson's disease group and the healthy control group [21]. A system was constructed using 3-axis piezoelectric element accelerometers, an analog-digital (AD) converter, and a personal computer (PC). Sensors were attached to the index finger and thumb that were performing the taps, and acceleration was recorded through a touch sensor. With the above system, it was possible to calculate the FTT quantitatively [22]. The thumb and index finger movements were measured during the FTT through a 9-degrees of freedom (DOF) sensor, and three-dimensional (3D) patterns were extracted [23]. However, these methods required the attachment of the sensor to the patient's body. Patients with impaired hands could have felt uncomfortable no matter how light the sensor was. In addition, non-attached systems are challenging to use in clinical practices since the sensors and cameras used are expensive.

Therefore, we quantitatively analyzed the FTT using artificial intelligence (AI)-Motion software (SW) in this study. Since this AI-Motion SW used a webcam, it was inexpensive, and it was possible not to cause any inconvenience to the patient. In addition, it was possible to calculate quantitatively the factors previously judged qualitatively. This approach allowed occupational therapists to identify areas that had not been previously identified and possibly reduce the variability in results depending on the occupational therapist's experience. The information extracted through this SW was able to distinguish between the young and elderly participants. Through these results, we tried to confirm whether quantitative analysis using AI could be applied to clinical practices.

2. Materials and Methods

2.1. Study Design

2.1.1. Participants

For the adult data, participants were recruited from a laboratory at the Wonju campus of Yonsei University. Data were recorded with a webcam which was installed in the laboratory. The elderly data were obtained from the Dong Yeosu Senior Welfare Center in Yeosu, Jeollanam-do. Due to the nature of the welfare center, there were not enough places to separately record the data from the elderly. Therefore, the researcher took videos with their cell phone. We collected data from a total of 30 adults and 30 older adults . However, some data were excluded due to three problems: video shake, coordinate loss, and data imbalance. Video shake was caused by using a handheld cell phone when recording the elderly data. Therefore, videos that were shaken a lot were excluded. The coordinate loss was similar to the case above. In some cases, the cell phone could not record the subject's whole hand since the cell phone was handheld. If the video had coordinate lost, the data were excluded. The last problem was data imbalance. In videos with data imbalance, there was no problem in terms of recording, but the subject did not perform the task properly. Videos with data imbalance were excluded since the data did not

Table 1. Characteristics of the participants.

Participants			Value
Elderly	Age	Mean	67.8 (2.7)
	Sex	Male	2
		Female	3
Adults	Age	Mean	24.75 (1.5)
	Sex	Male	3
		Female	5

come out accurately. Due to the above problems, even though we collected data from 30 elderly people and 30 adults, a total of 13 participants were included in this study. They were divided into five elderly and eight adults. The characteristics of the 13 participants are summarized in Table 1. The sample included adults and elderly participants who understood and consented to the purpose of this study. In addition, participants who had no restriction of knuckle movements and no hand tremors were included. This study was approved by Yonsei University Wonju Deliberation Committee (1041849-202108-BM-133-01).

2.1.2. Experimental Set-Up

Participants' hand motions were recorded through a webcam (C920 PRO HD webcam, Logitech, Swiss). Due to the nature of interdisciplinary convergence research, there was not enough time to use the system measured by other schools. Therefore, the hand motion of the elderly was recorded with the researcher's iPhone (iPhone 8+, Apple, CA, USA). In this study, the AI-Motion SW (www.neurorehap.com, South Korea) was run on a laptop (Legion Y720, Lenovo, China). The resolution of the recorded videos was 1280×720, and the frame rate was 30 Hz. The researcher set the camera so the participant could perform the task properly. The entire hand of the participant, including the wrist, was visible on the screen. When installing the camera, the camera lens was higher than the participant's hand position (Fig. 1). This camera height allowed the little finger to appear on the webcam.

2.1.3. Experimental Method

The participant was seated on a chair, and the researcher explained why the FTT was being filmed with a webcam. The researcher then demonstrated the operation of the FTT to the participant. The particiapant sat comfortably in a chair, put only their hands in the webcam's area of view, and avoided moving any part of their body other than their hands. After that, the recording proceeded, and the motion of touching the thumb and index finger in a sitting position was repeated ten times. The

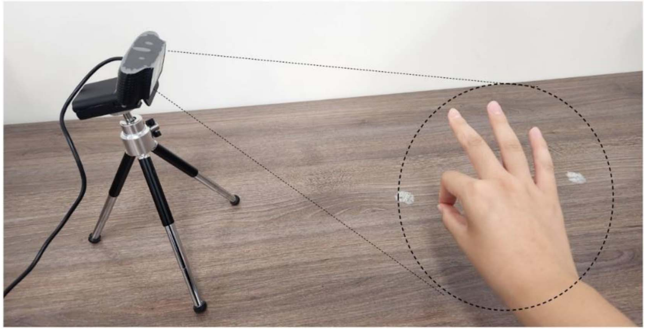

Fig. 1. (Color online) The camera settings environment. The webcam lens was pointed from top to bottom. All fingers and wrists were visible on the screen. If recorded from the side, the little finger may not be visible.

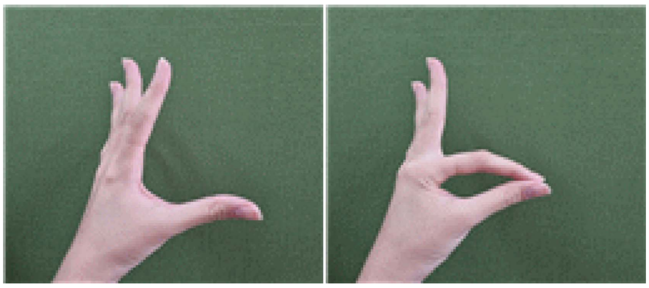

Fig. 2. (Color online) The FTT is a task in which the index and thumb are touched and released. During the task, participants should have moved their fingers as wide and as fast as possible.

FTT was first performed with the participant's dominant hand and then with their other hand (Fig. 2).

2.2. Proposed System

The processing process of the system proposed in this paper is shown in Fig. 3. After running the AI-Motion SW, the participant performed the task in front of the webcam. After the recording was finished, various elements were analyzed through the SW. Analyzable factors were distance, angle, time, and periodicity. The analyzed elements were saved and exported as a PDF. For the coordinate extraction, the core of the Mediapipe was employed. Additional analysis was conducted through the AI-Motion SW. There were a total of 21 coordinates in the hand. In the case of the FTT, since it was a task that moved the index finger and thumb, only six coordinates were used.

2.2.1. Angle Calculation

In this study, a total of six coordinates were used in Fig. 3 (0, 4, 5, 6, 7, and 8). Through these coordinates, it was possible to extract several elements from the FTT. Using

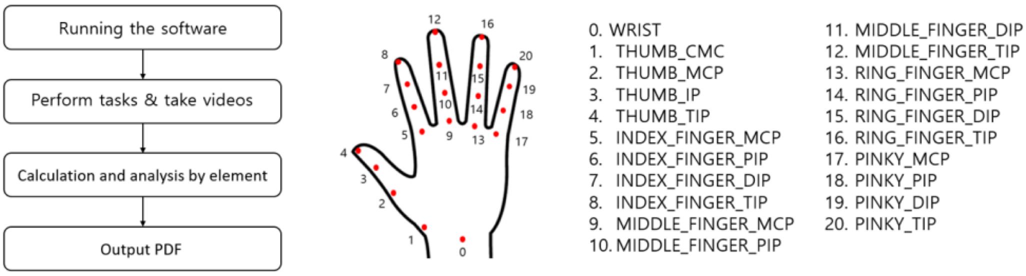

Fig. 3. (Color online) The software Process and Hand Landmarks. The FTT uses coordinates 0, 4, 5, 6, 7, and 8.

the Euclidean formula, the distance between the index finger and the thumb was calculated. Using these two vectors, the angle between the fingers was calculated. The angle was calculated using the vector dot product formula shown below.

$$\vec{a} \cdot \vec{b} = |\vec{a}||\vec{b}|\cos \quad (1)$$

$$\cos\theta = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} \quad (2)$$

$$|\vec{a}| = \sqrt{V_x^2 + V_y^2 + V_z^2} \quad (3)$$

$$\vec{a} \cdot \vec{b} = a_x b_x + a_y b_y + a_z b_z \quad (4)$$

2.2.2 Filtering

The calculated angles are displayed in a graph in Fig. 2. There was noise in the original signal in Fig. 2, and a median filter was used to smooth these signals (Fig. 2 Median Filtered Signal). The median filter is a function that finds the median of the signal and filters the noise of the signal smoothly. Since the frame rate was limited to 30 Hz in this paper, the signal was flattened using a 3-D median filter. The 3-D median filter used three windows, and by moving the windows one by one, the median value of the window was applied to the signal.

2.2.3. Interpolation

If the filtered signal was expressed as a stem type, it was seen that the amount of data was minimal. Since the frame rate of the videos used in this study was 30 Hz, this signal had a resolution of 0.03. However, it was difficult to calculate the time accuracy with a resolution of 0.03. Therefore, to increase the amount of data, spline interpolation was applied. As a result, it was possible to increase the resolution from 0.03 to 0.003, and the total amount of data increased about ten times. To apply the spline interpolation to the data, we used the cubic spline function in MATLAB. A spline function is a function in which 'sq' fills the empty space by matching 'x' and 'y'. In this paper, the value of 'xq' was set to 0.1. The empty spaces of 'x' and 'y' were filled in with 0.1 units. As a result of applying the function, the value of y increased by ten times.

2.2.4. Reference point setting & Judgement of operation and stop section

An operation section and a stop section of the signal were determined based on the increased data. A reference point was needed to judge the two sections. In this study, angular velocity was used as the standard. The formula below is the square of the angular velocity and is the formula to find the power of the angular velocity (AP). The AP is the amount of work produced per unit of time. Therefore, 'x' is the value of the angle obtained earlier, and 'y' is the AP of 'x.' A reference point was set to judge the operation and stop section of the task. The calculated average value of AP (APM) was set as the reference point. If the AP was greater than the APM, it was set to 500, and if it was less than the APM, it was set to 0. Zero indicated a stop section, and 500 indicated an operation section. Although each numerical value was used as a number, it was set to act as a number-based variable.

$$\omega = \left(\frac{\Delta\theta}{\Delta t}\right)^2 \quad (5)$$

2.2.5. Correction of operation and stop section.

During the analysis, when the interval between the signals was short, the interval was often not properly divided. Human hand gestures generally require a minimum amount of time to perform the action, and these physical movements are controlled by the brain. This time to perform the action is because the muscles contract and relax through nerve transmissions from the brain. Therefore, if an error occurred during the analysis, a function to correct this error was required. These errors also occurred when there was a sudden external or internal shock. For the correction, a variable called gap (minimum time required for a movement) was defined. When the change in motion was less than the gap, an Error Correction Function (ECF) was created to correct it to the state of motion before and after. The variable AR_C and the Pulseperiod function were used to distinguish the operation and stop sections in the corrected signal. Through the Pulseperiod function and the ECF, it was possible to detect the operation and stop sections in the signal.

3. Results

3.1. Angle Calculation

The original signal in Fig. 4 is the angle extracted through the SW. The Median Filtered Signal is a graph in which the median filter was applied to the original signal. As a result, the noise seen in the original signal disappeared. The signal's section is graphed, showing the operation section of the FTT. The part marked with a red circle (solid line) is the state in which the index finger and thumb were outstretched (OPEN). The part marked with a yellow circle (dashed line) is the state where the index finger and thumb were in contact (CLOSE). In the graph, OPEN is a total of nine times, and CLOSE is a total of ten times. The videos used in the analysis were of ten tapping motions, but there was a difference in the number of OPEN and CLOSE measurements. The reason for this difference was the starting position. The participant started the task with all their fingers extended. At this time, the part where the first finger was folded was the simple starting point, and the number of times was not counted. The count started from the part where the finger was folded. This study excluded the first part of CLOSE for analysis accuracy. Therefore, all the used and extracted values were nine in total.

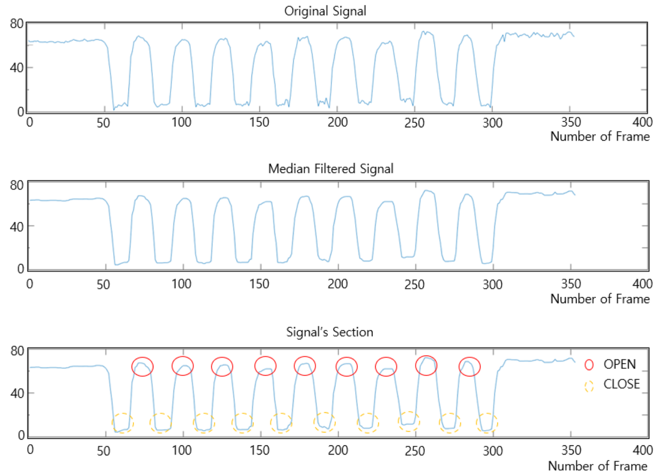

Fig. 4. (Color online) In the signal section, the red circles (solid line) are the OPEN sections, and the yellow circles (dashed line) are the CLOSE section. The number of OPEN sections is nine, and the number of CLOSE sections is ten. The reason for the difference in the number is that the participants started the task with their fingers extended. Since the unfolded part was recognized as the starting position, the count started from the folded part. Therefore, the number of CLOSE sections is one more than the number of OPEN sections. However, for the accuracy of the analysis, the first CLOSE section was excluded. Therefore, nine sections were used and extracted.

3.2. Interpolation

The original signal was the angle of the FTT extracted through the AI-Motion SW. Since the video frame rate was 30 Hz, the videos had a resolution of 0.03. For accuracy, the values of the data were increased ten-fold by interpolation. The 'interpolated result X 10' graph is a 10-fold increase from the original. There is an enlarged picture of a part of the original and interpolated signals at the far right of Fig. 5. In the case of the original signal,

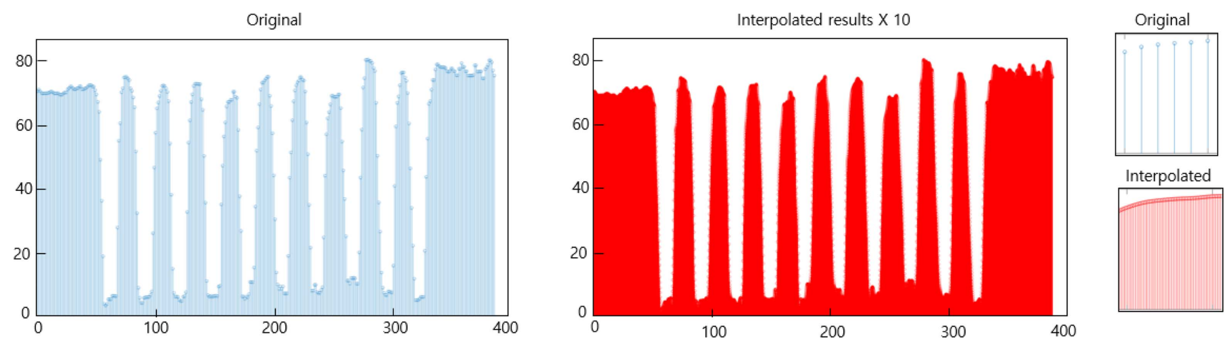

Fig. 5. (Color online) The original signal is the angle value of the FTT calculated through the SW. The interpolated data is ten-fold higher than the original signal. In the case of the original data, the data interval is wide, which means that the data is mostly empty. However, in the case of the interpolated data, the data gap is narrow. Since the amount of data was increased, a more accurate analysis is possible.

the data interval is wide; however, in the case of the interpolated signal, the data gap is tightly filled (Fig. 5). By increasing the resolution from 0.03 to 0.003, it was possible to analyze the data more accurately.

3.3. Reference point setting & Judgement of operation and stop section

Through the interpolation, the values of the data were increased ten-fold. The original number of frames was 400, which was increased to 4000 through the interpolation. The angle was also increased by ten-fold from the original value. The red line on the graph represents the angle, and the blue line represents the AP. The yellow pillar is the operation section of the task. The operation

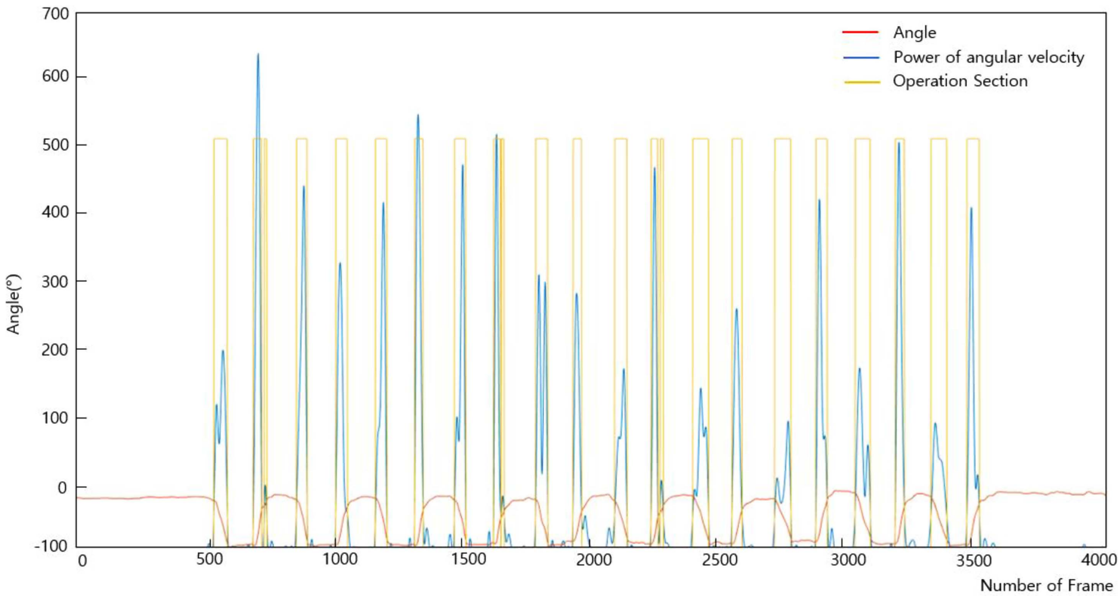

Fig. 6. (Color online) The x-axis and y-axis values increased ten-fold due to interpolation. The red line is the angle, the blue line is the power of the angular velocity, and the yellow pillars are the operation section.

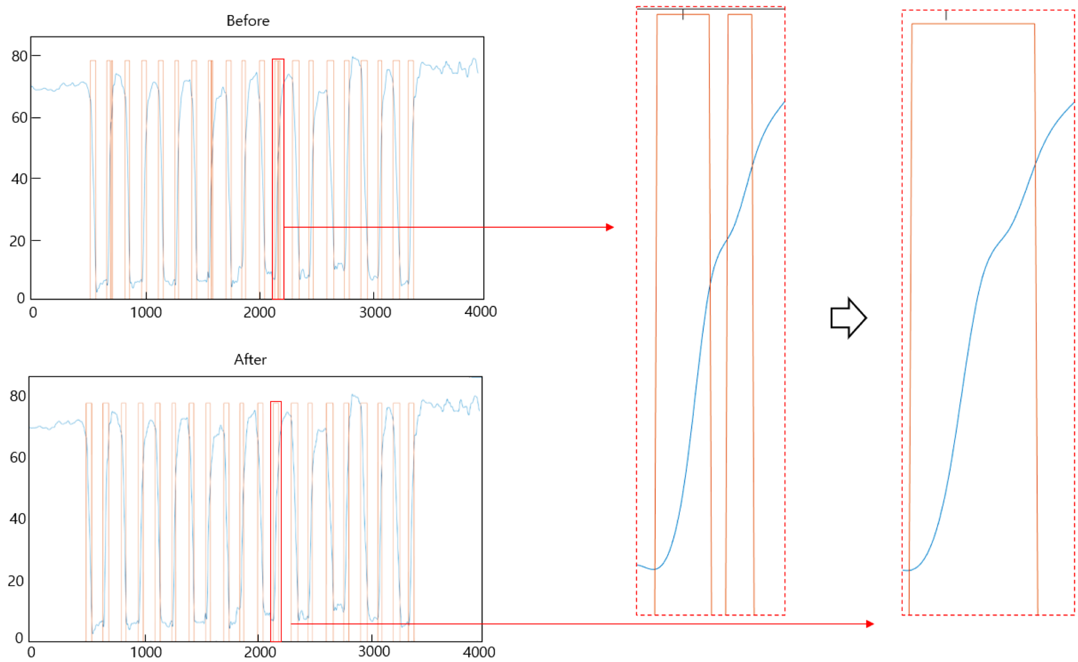

Fig. 7. (Color online) The Graphs before and after using the ECF. The 'before' is an uncorrected error and the 'after' has the error corrected.

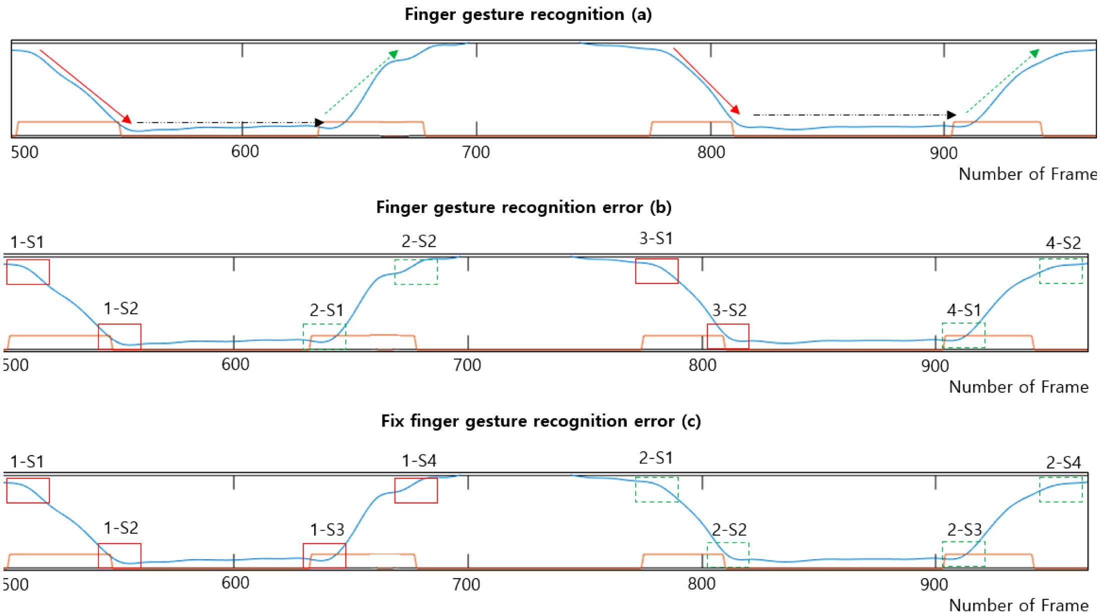

Fig. 8. (Color online) (a): The Finger gesture recognition. (b): The Finger gesture recognition error. (c): Fixed Finger gesture recognition error. The three arrows in (a) indicate task 1 time. However, in (b), there was an error, and task 1 time was recognized twice. Therefore, the error was corrected by correcting the data array. Figure (c) is the figure that correctly classifies the number of finger taps after the error has been corrected.

section of the task was detected through the AP; thus, the blue line and the yellow pillar are in the same place (Fig. 6).

3.4. Correction of operation and stop section

Figure 7 shows the result of using the ECF. In the figure, ‘before’ is an uncorrected error. These errors occurred when there was a sudden external or internal shock. The error was corrected through the ECF. In the figure, ‘after’ shows that the error has been corrected. As a result, it was possible to distinguish the operation and stop sections accurately.

3.5. Classification of finger motion state

If the motion and stop sections were determined from the data, then the finger motion status of the FTT was also determined. Fig. 8 shows the state of the finger motion. There are three arrows of different colors in the figure. The red line (solid line) is the section where the subject folded their finger, the black line (dashed line) is the section where the fingers were folded, and the green line (dotted line) is the area where the fingers were stretched out. The existing FTT recognizes folding and unfolding a finger once as a task. Therefore, the three arrows in Fig. 7(a) are recognized as one task. In the figure, the red square (solid square) represents when the task had been performed once, and the green squares (dashed squares) are when the task was done twice. However, in the case of Fig. 7(b), there are red and green squares in one task caused by an error that occurred where task one was incorrectly recognized as task two. This error could be corrected by simply changing the format of the data array. Fig. 7(c) is the figure with the error. By correcting the error, it was possible to distinguish the number of FTT operations. Table 2 summarizes the operation states of the FTT analyzed by the algorithm.

3.6. Analyzed characteristics and the Mann-Whitney U test

There are four parts that can be quantitatively analyzed in the FTT: distance, angle, time, and periodicity. Distance and angle are relative distances, and real angles are

Table 2. Organize finger movements.

Variable	Finger State
S1	Finger open
S1-S2	Folding finger
S2	Folded finger
S2-S3	Keep folded finger
S3	Folded finger
S3-S4	Stretching finger
S4	Finger open

Table 3. The mean and Mann-Whitney U test of the young and elderly participants for distance.

	Finger Index	Young	Elderly	*p*-value
Open Distance Mean (*SD*)	4-5	0.2825 (0.009)	0.2751 (0.111)	1.000
	4-6	0.3600 (0.018)	0.3139 (0.313)	0.515
	4-7	0.4170 (0.026)	0.3452 (0.147)	0.056
	4-8	0.4641 (0.033)	0.3770 (0.163)	0.032*
Close Distance Mean (*SD*)	4-5	0.2121(0.006)	0.1973(0.062)	0.841
	4-6	0.1725(0.018)	0.1593(0.062)	0.056
	4-7	0.1165(0.029)	0.1616(0.059)	0.032*
	4-8	0.0875(0.036)	0.1481(0.064)	0.008*

calculated when the index and thumb are folded and unfolded. Time is the total time taken when performing the FTT. Periodicity is an index indicating how periodically the FTT was performed. The periodicity could be calculated through the standard deviation of time (STD). It is judged that the lower the value of STD, the more periodic tapping was performed. The data from the young and elderly participants who performed the FTT were compared through a Mann-Whitney U test. The Mann-Whitney U test is a statistical test used to determine whether there is a difference between the means of two populations. It is a method to test the statistical significance of the difference regardless of the existence of a difference. When the *p*-value was less than 0.05, it was judged that there was a significant difference between the two groups.

3.7. The value of the four characteristics for the young and elderly participants

The 'Open distance' indicates the relative distance when the finger was opened in the FTT. The 'Close distance' is the relative distance when the finger was folded. The values written in the table represent the mean, and the values shown in parentheses are the standard deviation. In the table, if the Mann-Whitney U test value is less than or equal to 0.05, "*" is added next to it. From Table 3, it can be seen that there is a significant difference between the young and elderly participants. In Table 4, the 'open angle' is the angle when the finger was spread out, and the 'close angle' is the angle when the finger was folded. In the case of the angle, a significant difference was found in the open angle.

Table 4. The mean and Mann-Whitney U test of the young and elderly participants for angle, time, and periodicity.

	Young	Elderly	*p*-value
Open Angle Mean (*SD*)	53.8208 (6.4481)	37.2059 (17.6220)	0.008*
Close Angle Mean (*SD*)	19.2131 (6.9850)	16.2678 (6.5642)	0.095
nine times Tapping Time Mean (*SD*)	8.4963 (0.5210)	10.2220 (0.9390)	0.056

3.8. Error-bar

Figures 9 and 10 are charts with error bars added to the bar charts. The blue bar indicates the youth data, and the red bar indicates the elderly data. The black line above the bar indicates the standard deviation. The longer the black line, the larger the standard deviation. Overall, in the case of the young participants, the standard deviation line is short. However, for the elderly participants, the line

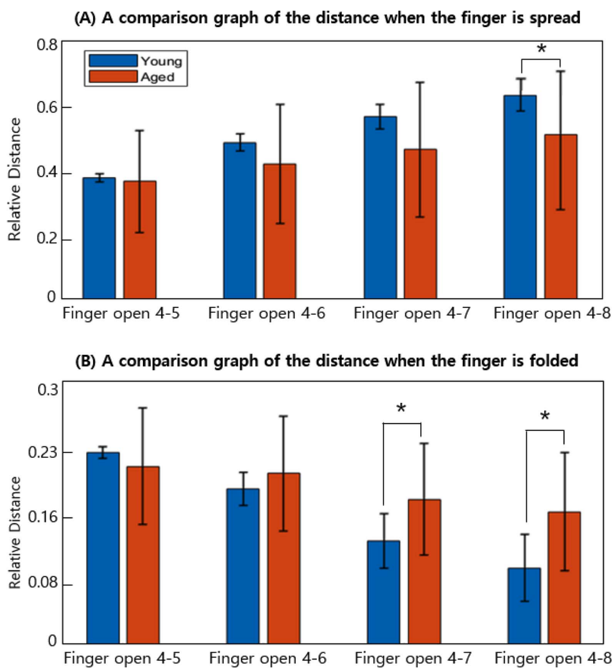

Fig. 9. (Color online) (A) A comparison graph of the average distances between the young and elderly group when the fingers were spread and the group averages of the young and elderly participants; (B) A comparison graph of the average distances between the young and elderly group when the fingers were folded.

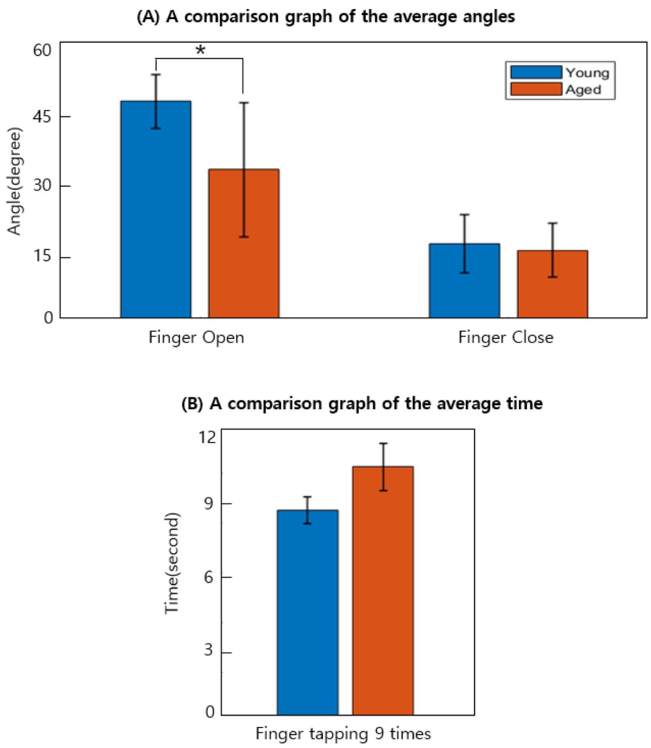

Fig. 10. (Color online) (A) A comparison graph of the average angles when fingers were folded and unfolded between the young and elderly groups. (B) A comparison graph of the average times it took to tap the finger nine times between the young and elderly participants.

is very long. This means that the reproducibility of the elderly participants is lower than young participants. The part marked with "*" in the graph is the part with a *p*-value of 0.05 or less, calculated by the Mann-Whitney U test. The results below confirmed that there was a difference in the 4-7 and 4-8 distances where the fingers were spread and closed. In the angle part, a significant difference was found when the fingers were spread out.

4. Discussion

The purpose of this study was to investigate whether the FTT could be quantitively analyzed through a 3D motion analysis program (AI-Motion SW). In addition, the participants were classified into two groups, young or elderly, based on their age, and the results of the FTT by age were compared and analyzed. By dividing and analyzing the participants by age, it was possible to objectively analyze the relationship of aging, a characteristic of Parkinson's disease.

In this study, the finger width, the decrease in frequency, and the increase in speed, evaluated by the observations of previous therapists, were objectively evaluated using the means and standard deviations [11]. Therefore, the characteristics of Parkinson's patients could be objectively evaluated through three items, which are characteristics of bradykinesia, the reduction of automatic movement, the difficulty initiating movement, and the general slowness in physical action. As a result of analyzing the distance between the fingers of the elderly and young participants, significant results were obtained when the fingers were spread apart and in contact at time points 4-7 and 4-8 ($p < 0.05$). As a result of the analysis of the 'Hand motion,' analyzed through the FTT test, when analyzing the distance, the distance between the fingers of the young participants was larger than that of the elderly participants.

In addition, when angle, time, and periodicity were analyzed, The young participants' results showed a larger angle between the fingers than the elderly participants, and the periodicity of tapping the fingers was shorter. These results found that the elderly participants' 'Hand motion' was lower compared with the young participants. Through this, it was obtained that although this study was conducted on normal people, the difference between adults and the elderly could be distinguished. These results will likely be useful when confirming the applicability of hand function evaluations in patients with brain damage in the future. The results of this study can quantify the clinical characteristics of the participant by providing objective values and provides various information about the patient's movements.

In a previous study, it was confirmed through a 3D motion analysis program that there was a significant difference between Parkinson's disease patients and normal people during the FTT. In this study, it was confirmed that the participants could be evaluated quantitatively by the FTT. In future research, it would be possible to increase the number of participants and to measure bradykinesia in various body parts by tests other than finger tapping by brain stimulation therapy, such as transcranial magnetic stimulation (TMS) or transcranial direct current stimulation (tDCS). In fact, it is a challenge to estimate a subtle motion change in patients after brain stimulation therapy by the human eye. Nevertheless, the result of this study suggests that it is possible to employ a developed program for quantitative motion analysis during brain stimulation therapy.

5. Conclusion

In this study, an FTT was quantitatively evaluated using AI-Motion SW. The distance, angle, time, and periodicity could be calculated from the FTT. The characteristics and differences between the young and the elderly participants were distinguished through the calculated values. Among them, there was a difference at distances 4-7 and 4-8 when the fingers were spread and folded. When the fingers were spread, the difference was confirmed by the angle. Through these results, it was found that AI could quantitatively analyze clinical tasks. If the problem of a single camera is solved, we believe that quantitative evaluations using an AI will be applicable to clinical practices in the future.

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