Fluctuation Analysis of Repetitive Writing Motion by Using DFA

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***Abstract*—Control of voluntary movements is a dual structure of cognitive and the physical controls. Cognitive control involves attentional resources, whereas physical control does not. Various voluntary movements can be performed by combining cognitive and physical controls. If these two controls could be separated, we would be able to predict the level of acquisition of physical exercise skills from the expenditure of attentional resources. The relationship between repetitive body movements and attentional resources has already been investigated using synchronous tapping methods. Body movements that depend on attentional resources are performed by cognitive control, and synchronous errors fluctuate with white noise. The fluctuations of the synchronous errors gradually shift to the one-over-f fluctuation, as the dependence on the cognitive control in the body movement decreases. We are able to estimate the control system related to the body movements of synchronous tapping using the fluctuation features of the synchronous error time series. In our previous study, we reported that a time series of the handwriting time element (HTE) contains self-similarity features, and the detrended fluctuation analysis (DFA) was applied to the analysis of the self-similarity at the time. As a result of examination, if the time series of the HTE had self-similarity, it implied that this time series did not have a fixed timescale. Some previous studies reported a crossover phenomenon associated with a change in the short- and long-range self-similarity features during the DFA. We investigated the relationship between the local self-similarity on the timescale and the differences in the difficulty levels for writing Kanji characters by hand. Therefore, in this study, we focus on the differences of fluctuations for the local tasks constituting synchronous writing tasks. For the purpose of investigation, we evaluate the difference of coping strategies when writing Kanji characters repeatedly, using relationship between fluctuations of body movements and attentional resources.**

***Index Terms*—one-over-f fluctuation, handwriting, Kanji character, attentional resource, coping strategy**

I. Introduction

Control of voluntary movements is a dual structure of cognitive and physical controls. Cognitive control involves attentional resources, whereas physical control does not. Various voluntary movements can be performed by combining cognitive and physical controls. If these two controls could be separated, we would be able to predict the level of acquisition of physical exercise skills from the expenditure of attentional resources. The relationship between repetitive body movements and attentional resources has already been investigated using synchronous tapping methods [1] [2]. Action timing must be anticipated for the synchronous tapping task. It is possible to estimate a control system related to the body movements of synchronous tapping using the fluctuation features of the synchronous error time series. Body movements that depend on attentional resources are performed using cognitive control. Synchronous errors fluctuate with white noise. Fluctuations of the synchronous errors time series were found to gradually shift to the one-over-f fluctuation, as the dependence on the attentional resources in the body movement decreases. Detrended fluctuation analysis (DFA) is an effective method used for analyzing physiological signal fluctuations because it needs only a few rigid assumptions regarding signal stationarity [3]. If the signal time series has self-similarity, it is interpreted as covering all timescale. However, in many cases, the same self-similarity is not considered to cover the entire timescale in the time series of actual systems. Some previous studies reported a crossover phenomenon associated with a change in the short- and long-range self-similarity features during the DFA [4].

In our previous study, we reported that a time series of the handwriting time element (HTE) contains self-similarity features [5] [6] [7]. It was difficult to ensure the correct stationarity of the HTE time series; therefore, we used the DFA method. Furthermore, we investigated the relationship between the local self-similarity on the timescale and the differences in the difficulty levels for writing Kanji characters by hand. In this study, we focus on the differences of fluctuations for the local process constituting synchronous writing one Kanji character. For the purpose of investigation, we evaluate the difference of coping strategies when writing one Kanji character repeatedly, based on the relationship between fluctuations of body movements and attentional resources. The coping strategy here means something like that subject's peculiarity when writing that one letter. The specific task of repetitive body movements is to write specific Kanji character by hand. That is, the task is repetitive writing of each of five kinds of Kanji characters; 'den', 'tsu', 'ki', 'dai', and 'ichi'. These five Kanji characters have slightly different difficulty levels; from "Very hard" to "Very easy". Depending on the difficulty of handwriting, coping strategies for handwriting have been expected to change.

II. Experiment method

Fig. 1 shows the experimental protocol. First, we performed

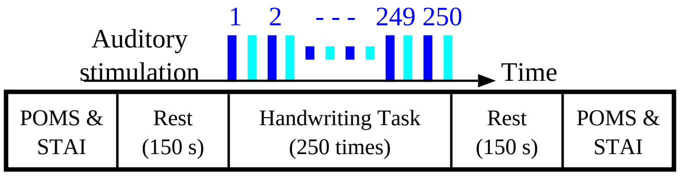

Fig. 1. Experimental protocol.

tests comprising the profile of mood states (POMS) and the state-trait anxiety inventory (STAI); second, the subjects were required to close their eyes and rest for 150 s before being asked to perform the assigned handwriting tasks; third, the tests were repeated after the 150 s rest. These steps were repeated by them with enough breaks and comprised one set of the experimental process. A dual-task method was applied in this experiment. This method involved synchronization tapping and handwriting tasks.

Fig. 2 shows the configuration of the experimental system. The handwriting field was set on a pen tablet. This field was

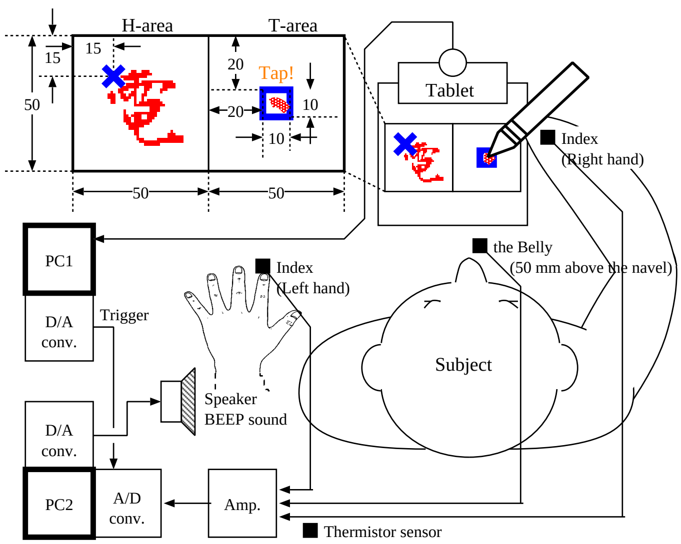

Fig. 2. Experimental system.

a square area (H-area) with a side 50 mm on the left and a square area (T-area) with a side 10 mm on the right. The "x" mark was drawn in the H-area. We maintained the auditory stimulus until the end of the task according to the repetitive periods (interstimulus interval ISI) detected by the preliminary experiment. Auditory stimulus was a beep sound with a time length of 20 ms. The subjects were required to start writing a character with the first auditory stimulus from the "x" mark on the H-area. When they finished writing a character, they tapped the T-area using their pen tips such that they were in synchrony with the second auditory stimulus in the best possible manner. One trial is from the rise of the first auditory stimulus to the immediately before next rise of the first auditory stimulus. 250 consecutive trials were carried out, which comprised one set. The HTE is divided into six components (i.e., SLs, SLe, LsT, LsLe, LeT, and ST), which could be obtained from one trial. One set consisted of 250 trials, and 250 samples are

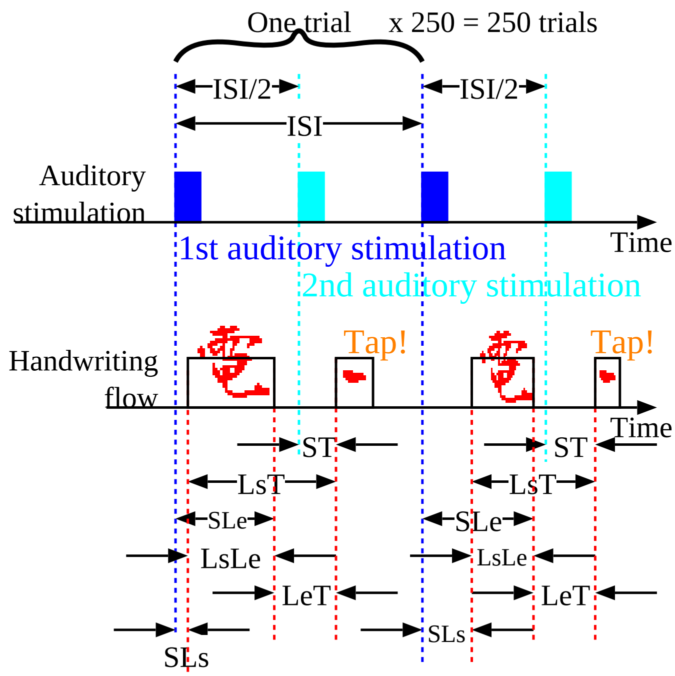

Fig. 3. Six kinds of handwriting time elements.

obtained in each HTE. Each time series of the HTE consisted of 250 samples. The status of the subject's autonomic nervous system activation during the experiment was monitored by three contact temperature sensors worn on the trunk (near the umbilicus) and both index fingers. At the present time, we do not know how to extract information related to writing a Kanji character from activation of autonomic nervous system, so we do not discuss it in this report.

TABLE I shows the handwriting task. Five Chinese Kanji characters were selected for the handwriting task. These characters, 'den', 'tsu', 'ki', 'dai', and 'ichi', has slightly different difficulty levels; "Very hard", "Hard", "Middle", "Easy", and "Very easy", and their stroke counts are different. Then, the stroke count was chosen as the index of task difficulty. The slight differences between character shapes were regarded as the difference of difficulty between handwriting tasks; the stroke count is an index of the handwriting difficulty.

III. Analysis Method

The time series of the HTE is represented by $x_i(i = 1, 2, 3, \cdots, N-1, N)$; then, x_i is the intended signal of the DFA where N was 250 samples of the HTE, that is, $N = 250$. The time series $y_k(k = 1, 2, 3, \cdots, N-1, N)$ of the cumulative sum for x_i was computed as $\sum_{i=1}^{k}(x_i - \overline{x})$, where $\overline{x}$ was a mean value of x_i. $y_n^*(k)$ is the regression line of the time series $\{y_k, y_{k+1}, y_{k+2}, \cdots, y_{k+n-2}, y_{k+n-1}\}$ where n was the timescale and $n = 3, 4, 5, \cdots, N-1, N$. The slope of the regression line on the log-log scale field of the $F(n)$-n

TABLE I
FIVE KINDS OF HANDWRITING TASKS

Pronunciation	Character shape	Stroke count	Handwriting difficulty
den	電	13	Very hard
tsu	通	9	Hard
ki	気	6	Middle
dai	大	3	Easy
ichi	一	1	Very easy

characteristic defined by (1) is called the scaling index β in the DFA.

$$F(n) = \sqrt{\frac{1}{N}\sum_{k}\left(y_k - y_n^*(k)\right)^2} \tag{1}$$

This general shape of the $F(n)$-n characteristic is curved in this study. That is called the crossover phenomenon in general. In order to avoid the problem of this crossover phenomenon, we were focusing on the local trends, that is, the $\frac{\Delta F(n)}{\Delta n}$-$n$ characteristics on the log-log scale field where Δ was the first-order difference operator. However, the $\frac{\Delta F(n)}{\Delta n}$-$n$ characteristics was very noisy in this study. So, we have proposed the characteristics of the modified local trends. That is the $L\beta_m$-m characteristics where $L\beta_m$ was the slope of the regression line when $F(n)$-n is log-log plotted in the timescale interval $[3, m]$ where m was the timescale and $m = 4, 5, 6, \cdots, N-1, N$. For example, in the condition of $m = N$, (2) is established

$$L\beta_m|_{m=N} = \beta. \tag{2}$$

Here, the subscript hte and knj is attached to $L\beta_m$, and ${}_{hte}L\beta_m^{knj}$ represents the $L\beta_m$ value of hte ($hte =$ SLs, SLe, ST, LsLe, LsT, LeT) on each knj ($knj =$ den, tsu, ki, dai, ichi). Moreover, the vector $\mathbf{LB}_m^{knj}$ is a set of ${}_{hte}L\beta_m^{knj}$ values when the timescale is m in a Kanji character knj as shown (3).

$$\mathbf{LB}_m^{knj} = \{{}_{\mathrm{SLs}}L\beta_m^{knj}, {}_{\mathrm{SLe}}L\beta_m^{knj}, {}_{\mathrm{ST}}L\beta_m^{knj}, {}_{\mathrm{LsLe}}L\beta_m^{knj}, {}_{\mathrm{LsT}}L\beta_m^{knj}, {}_{\mathrm{LeT}}L\beta_m^{knj}\} \tag{3}$$

The HTEs indicating the maximum and minimum of the six components in $\mathbf{LB}_m^{knj}$ are extracted as ${}_{max}hte_m^{knj} = \arg\max_{hte} \mathbf{LB}_m^{knj}$ and ${}_{min}hte_m^{knj} = \arg\min_{hte} \mathbf{LB}_m^{knj}$, respectively. Furthermore, the standard deviation of the six components in $\mathbf{LB}_m^{knj}$ is calculated as σ_m^{knj}. If the σ_m^{knj} value is larger, the fluctuation characteristics of the two HTEs ${}_{max}hte_m^{knj}$ and ${}_{min}hte_m^{knj}$ will be more different on this timescale m. On the other hand, if the σ_m^{knj} value is small, the fluctuation characteristics of the six HTEs are similar on m. Based on the two HTEs ${}_{max}hte_m^{knj}$ and ${}_{min}hte_m^{knj}$ to be extracted and σ_m^{knj} to be calculated, a coping strategy common to the subjects for the handwriting of that Kanji character knj is estimated. If it is interpreted that the ordinary scaling index β is an evaluation index of fluctuation covering the entire timescale, the proposed $L\beta_m$ is able to interpret as an evaluation index of fluctuation in the local timescale. Since ${}_{max}hte_m^{knj}$ and ${}_{min}hte_m^{knj}$ are ${}_{max}hte_m^{knj} \geq {}_{min}hte_m^{knj}$ according to the definition, ${}_{min}hte_m^{knj}$ tends to be relatively white noise than ${}_{max}hte_m^{knj}$. That is, ${}_{min}hte_m^{knj}$ is able to interpret as a more cognitive element than ${}_{max}hte_m^{knj}$. Furthermore, if ${}_{max}hte_m^{knj}$ or ${}_{min}hte_m^{knj}$ common to subjects is found on a specific timescale, the tendency of the fluctuation is able to interpret as specific coping strategy in the handwriting of that knj.

IV. Results and Discussion

Fig. 4 shows six types of HTE values measured from five subjects; sub. A, B, C, D, and E. The columns of graphs

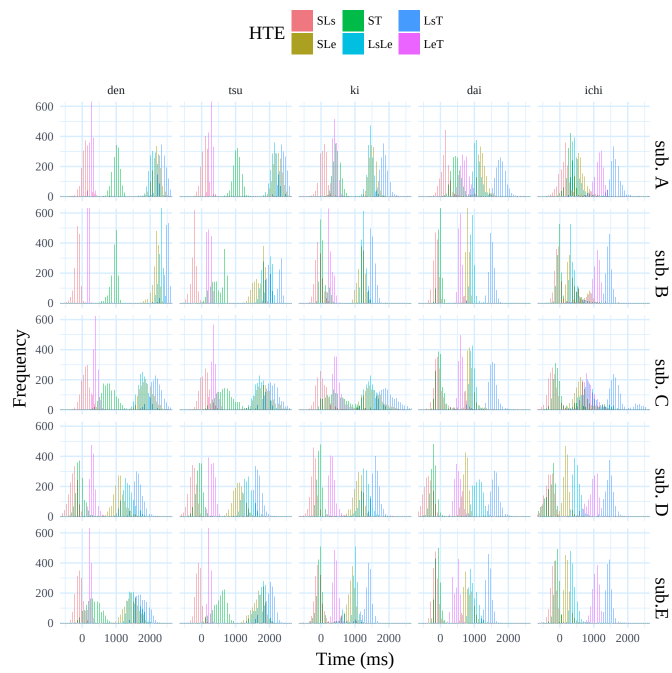

Fig. 4. Histogram of measured HTEs.

arranged in 5×5 are five Kanji characters, the rows are five subjects. The horizontal axis of each graph is a time (ms), bins of width 100 ms are set, and the number of occurrences of HTE values in each bin is the vertical axis.

Fig. 5 shows (a)$F(n)$-n characteristics (upper figure) and (b)$L\beta_m$-m characteristics (lower figure) of the six HTE time series measured by subject A (sub. A in Fig. 4), respectively. Although the $F(n)$ value of LeT is smaller than the other five types of HTE, the point to be noticed here is the slope of the $F(n)$-n characteristics. The slope of the regression line of the $F(n)$-n characteristic is the scaling index in the DFA, and the plot value of $m = 250$ on the $L\beta_m$-m characteristic represents this index. In the $F(n)$-n characteristics, the gradient differences between the six HTEs are confirmed. On the other hand, it is obvious from this figure that the scaling index is not constant at any HTE. It is possible to

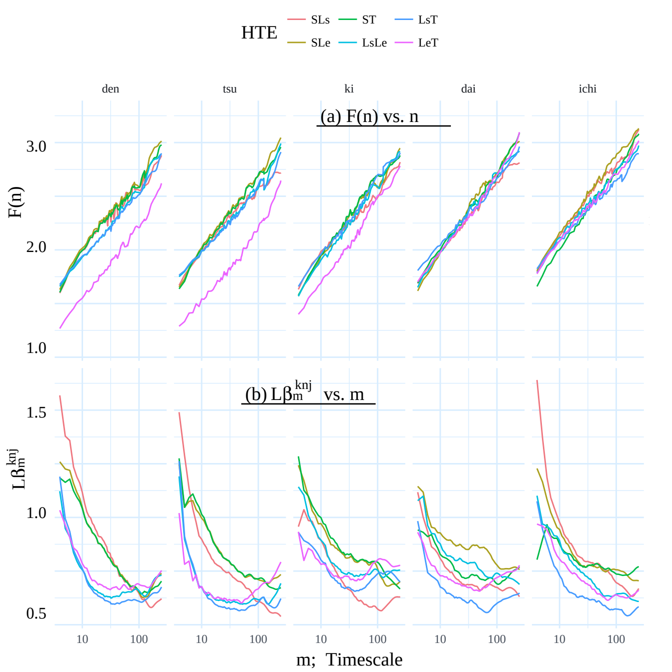

Fig. 5. (a)$F(n)$-n characteristics and (b)$L\beta_m$-m characteristics.

calculate the difference value of $F(n)$-n characteristic in order to capture the trend of the local scaling index with respect to m, but this trend is very noisy and confuses our interpretation. The $L\beta_m$-m characteristic proposed by this research seems to visualize local trends of the scaling index along the $F(n)$-n characteristic.

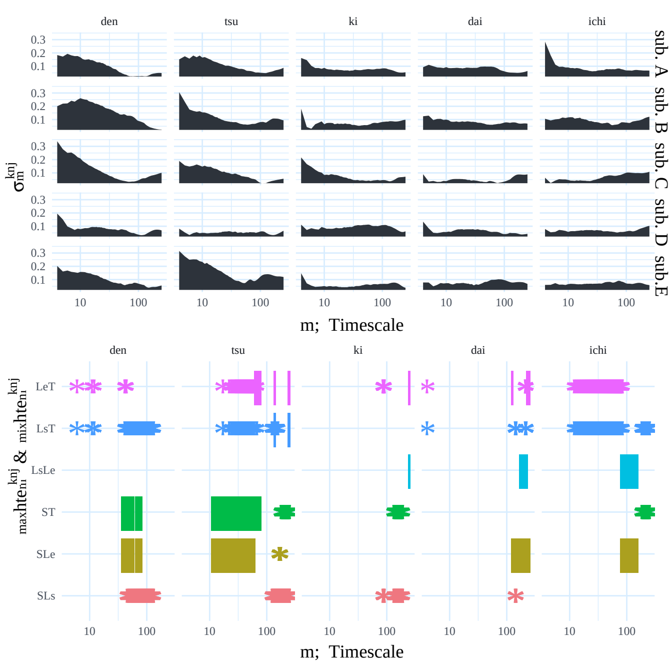

Fig. 6. σ_m^{knj}-m characteristics and $_{max}hte_m^{knj}$&$_{max}hte_m^{knj}$-m characteristics.

In Fig. 6, the upper graphs are the σ_m^{knj}-m characteristics and the lower graphs are the $_{max}hte_m^{knj}$&$_{min}hte_m^{knj}$-m characteristics. Graphs of the σ_m^{knj}-m characteristics are arranged for each subject and for each knj. The horizontal axis is m, and the vertical axis is σ_m^{knj}. The lower graphs in this figure focuses on the variety of $_{max}hte_m^{knj}$ or $_{min}hte_m^{knj}$ extracted from five subjects. This graph was plotted with a vertical bar or an asterisk on m in which five HTE types measured from five subjects were common to five subjects or limited to two types. A vertical bar represents $_{max}hte_m^{knj}$ and an asterisk represents $_{min}hte_m^{knj}$. The horizontal axis is m, and the vertical axis is six kinds of the HTE. The σ_m^{knj}-m characteristics seem to be flat as the difficulty level of knj goes down. This implies that, on lower difficulty levels, the six components of $\mathbf{LB}_m^{knj}$ have nearly identical values on any timescale. There is no room to include various coping strategies in the handwriting of simple Kanji character. It is interpreted that handwritten execution of simple Kanji character is executed by very simple coping. A very simple coping may be interpreted as a physical process. That is, the coping strategy is associated with attentional resources assignment.

V. Conclusion

In this report, we evaluated the difference of coping strategies when writing Kanji characters repeatedly, using relationship between fluctuations of body movements and attentional resources.

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