

Fractal Dimension Analysis of NIRS Time-series Data during a Mental Arithmetic Task

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Abstract—Near-infrared spectroscopy (NIRS) is a method that uses the near-infrared band of the electromagnetic spectrum. Currently, brain-computer interfaces (BCIs) using NIRS are being actively studied. Classifying NIRS time-series data according to mental concentration or relaxation is useful for BCI systems. In this study, we used NIRS to measure changes in oxygenated hemoglobin concentration during a mental arithmetic task. We then estimated the correlation dimension and the Higuchi fractal dimension from the NIRS time-series data. As a result, the correlation dimension and the Higuchi fractal dimension during a mental arithmetic task were found to be higher than those during relaxation in most of the NIRS measurement channels.

1. Introduction

Integrated functions of the brain such as cognition and recollection involve the complexity of the cerebral cortex, which performs a variety of information processing tasks [1]. Chaotic time-series analysis is therefore necessary for evaluating complex brain systems. It is also necessary to improve the intermediation accuracy of intention and information between humans and machines to grasp human mental activity accurately. Mental arithmetic is typical mental work requiring attention and concentration. Prior research demonstrates that during such typical mental work there is increased cerebral blood flow in the frontal area of the brain [2], where there is also a difference in Lyapunov exponents between discomfoting tasks and relaxation [3]. Therefore, we measured changes in oxygenated hemoglobin concentration during a mental arithmetic task using near-infrared spectroscopy (NIRS) and calculated the correlation dimension (CD) and the Higuchi fractal dimension (HD) from the resulting time-series data.

2. Near-infrared spectroscopy

NIRS is used to measure variation in oxygenated hemoglobin concentration caused by oxygen metabolism in brain blood flow associated with neural activity. Hemoglobin in the blood scatters light, and the hemoglobin accompanied by oxygen changes the levels of absorption and scattering. NIRS detects the levels of

absorption and scattering and thereby measures the changes in concentration of oxygenated hemoglobin. NIRS uses light with wavelengths of about 700–900 nm. Near-infrared light is difficult to transmit through the human head. One solution is using optical fibers for intracerebral irradiation from the surface of the head; absorbed and scattered light in the cerebral cortex converges in the optical fiber, which is located about 30 mm from the irradiated point on the head surface. Then, light reaches depths of about 20 mm from the surface of the head and is absorbed by hemoglobin in the cerebral cortex. A portion of the scattered light reaches an optical fiber, and is then guided to a photomultiplier and converted into an electrical signal.

3. Correlation Dimension

The method of Grassberger and Procaccia [4] reconstructs single-variable time-series data to higher-dimensional space by using the embedding theorem to calculate CD, which represents the characteristic of the attractor. To plot N data points in m -dimensional space by the embedding theorem, each data set reconstructed in shifting time is represented as a vector X_i . The distance from X_i to each of the remaining $(N - 1)$ points is calculated. Data points within a scale r are counted, and this process is iterated against each point. This gives a statistic called the correlation sum. The correlation sum at scale r for a given embedding dimension is defined as

$$C^m(r) = \lim_{n \rightarrow \infty} \frac{1}{N^2} \sum_{\substack{i,j=1 \\ i \neq j}}^N I(r - |y_i - z_j|), \quad (1)$$

$$D^m(r) = \frac{\log C^m(r)}{\log r}. \quad (2)$$

Displacement vectors y_i and z_i are given by

$$\begin{cases} y_i = X_{ki} - X_t, \\ z_i = X_{ki+s} - X_{t+s}. \end{cases} \quad (3)$$

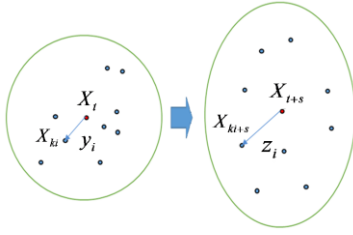


Fig. 1 Displacement after S seconds.

An attractor point at a specific time t and the corresponding time-series data are given by

$$\begin{cases} X_1 = (\xi_1 & \xi_{1+\tau} \dots \xi_{1+(m-1)\tau}), \\ X_2 = (\xi_2 & \xi_{2+\tau} \dots \xi_{2+(m-1)\tau}), \\ \vdots \\ X_t = (\xi_t & \xi_{t+\tau} \dots \xi_{t+(m-1)\tau}). \end{cases} \quad (4)$$

Here, the following notations are used:

- $\xi_1 \xi_2 \xi_3 \dots \xi_t$: time-series data,
- τ : time lag,
- m : embedding dimension,
- X_t : attractor point at time t ,
- X_{k_i} : other attractor points in a hypersphere with radius r and center point X_r .

C^m is the correlation sum, D^m is CD, $I(t)$ is the Heaviside function, and N is the number of neighborhood points.

4. Higuchi Fractal Dimension

The Higuchi fractal dimension HD is calculated using a non-parametric time-series analysis method[5]. A peculiarity of this analysis technique is the use of pattern recognition when series figures drawn in a plane are heterogeneous. The length of the curve indicated by the time series on the graph is therefore defined as a function of time t , which can be a coarse time series. Furthermore, when the length of the curve shows a fractal nature, such as $\langle L(\tau) \rangle \propto \tau^D$, we can define the fractal dimension of the time-series data to characterize the data's turbulence. In other words, if a point $(\log \tau, \log \langle L(\tau) \rangle)$ travels a straight line over the analysis object's time scale $\tau_{\min} \leq \tau \leq \tau_{\max}$, then the time-series data at this time scale may be fractal. The curve length is then

$$\Delta_t L(\tau) = \frac{1}{N-1} \sum_{k=1}^{N-t} \left\{ \sum_{i=1}^{\left\lfloor \frac{N-k}{t} \right\rfloor} |X_{k+it} - X_{k+(i-1)t}| \cdot \frac{\left\lfloor \frac{N-k}{t} \right\rfloor t}{N-1} \right\} \quad (6)$$

and HD is

$$D = - \frac{\log \Delta_t - \log \Delta_{t-1}}{\log t - \log(t-1)} \quad (7)$$

Here, N is the number of data points, t is $\{1, 2, 3 \dots N/2\}$, k is the time interval, time series X is $\{x_1, x_2, \dots, x_N\}$, D is HD, and $\lfloor \cdot \rfloor$ is Gauss' notation.

5. Experiment and analysis

We measured changes in oxygenated hemoglobin concentration during a mental arithmetic task using NIRS. Fig. 2 shows the block design for this experiment. One operation consists of 30 s of rest, followed by a 30-s task, and then 10 s of rest. This operation is repeated five times. The task is mental arithmetic work, iteratively subtracting 13 from a random value over 500 up to 1000. The random value is given to participants just before the experiment. During the pre- and post-task rest periods, participants are asked to relax as much as possible. The frontal area of the brain is measured over 22 channels with a 3×5 probe arrangement (Fig. 3) based on the 10–20 electrode system. Participants were 4 healthy men in their 20s. The study was approved by the ethics committee of Tokyo Denki University and was conducted in accordance with the current version of the Declaration of Helsinki. All participants gave informed consent after the study was explained to them.

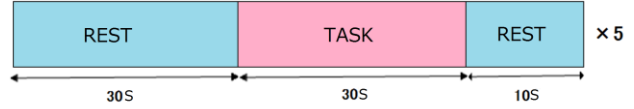


Fig. 2 Block design.

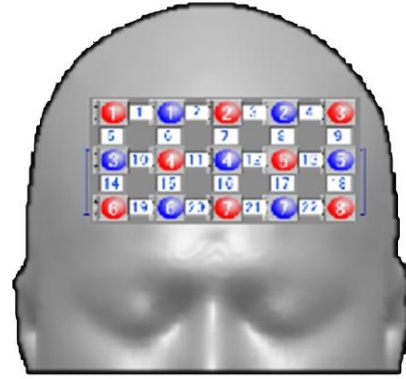


Fig. 3 Channel locations.

To remove noise from the measured NIRS time-series data we applied a fourth-order low-pass filter to the data and used the Student's t -test ($p = 0.05$). We then calculated CD and HD from the concatenated NIRS time-series data during five task periods. The same calculations were performed for the rest periods.

6. Results

Figs. 4 and 5 show the results for CD and HD in each

channel for participant C. CD was higher during the task than during rest in 18 of the 22 channels. HD was higher during the task than during rest in 19 of the 22 channels.

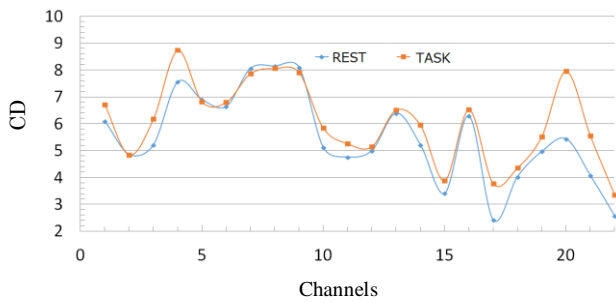


Fig. 4 CD for participant C in each channel.

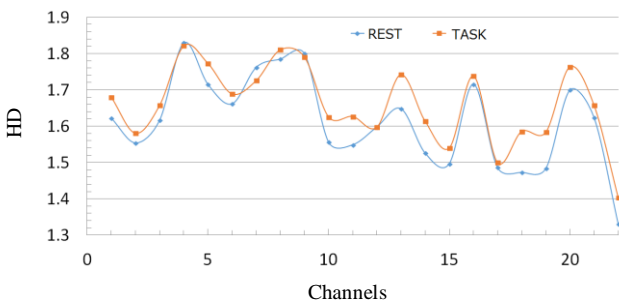


Fig. 5 HD for participant C in each channel.

Fig. 6 shows the average and standard deviation of CD over all channels for each participant. For all the participants, CD was higher during the task than during rest, but there was no significant difference between the task and rest.

Fig. 7 shows the average and standard deviation of CD over selected channels for each participant. Although channels are selected and CD was higher during the task than during rest, no significant difference was found between the task and rest.

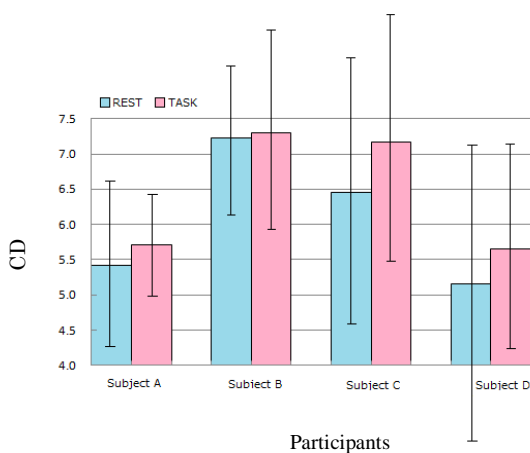


Fig. 6 Average and standard deviation of CD over all channels for each participant.

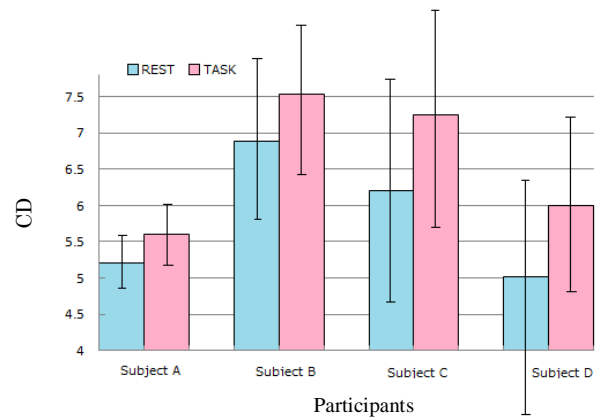


Fig. 7 Average and standard deviation of CD over selected channels for each participant.

Fig. 8 shows the average and standard deviation of HD over all channels for each participant. HD was higher during the task than during rest in 3 of the 4 participants. These differences between the task and rest were significant in the 3 participants.

Fig. 9 shows the average and standard deviation of HD over selected channels for each participant. HD was higher during the task than during rest, and there was a significant difference in the average between the task and rest in 3 of the 4 participants.

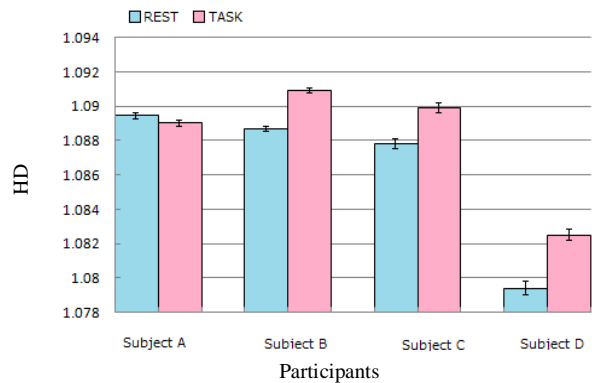


Fig. 8 Average and standard deviation of HD over all channels for each participant.

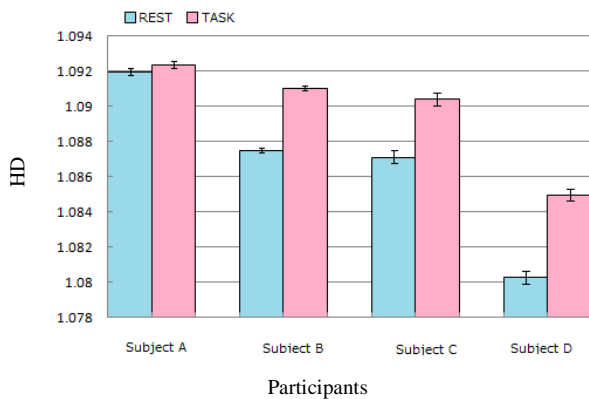


Fig. 9 Average and standard deviation of HD over selected channels for each participant.

6. Conclusion

We measured variation of oxygenated hemoglobin concentration during a mental arithmetic task by using NIRS and calculated CD and HD from time-series data for 4 participants. In most channels, CD and HD were higher during the task than during rest for all participants.

A significant difference in HD was found between the task and rest in 3 of the 4 participants. This may suggest that HD is more effective than CD for distinguishing between mental tasks and relaxation. We will increase the number of participants in future experiments. Here, we calculated CD and HD from the concatenated NIRS time-series data during five operations.

We will also plan to calculate CD and HD from the averaged NIRS time-series data during of five operations in future work.

● Acknowledgments

This work was supported in part by JSPS KAKENHI Grant Number 25420385.

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