

Trial on Low-Pass Filter Design for Bio-Signal Based on Nonlinear Analysis

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(Received January 22, 2019; Accepted July 11, 2019)

The nonlinearity of the mathematical model describing the cerebral blood flow dynamics and the body sway in the prefrontal cortex was investigated experimentally. The measured bio-signal data were smoothed with each low-pass filter. The signal was set to 0.1–2 Hz for the cerebral blood flow dynamics and to 0.1–20 Hz for the body sway. Nonlinearity was observed in the biological signal when the cut-off frequency of the low-pass filtering was 0.2 Hz or less, and while the body sway was 0.5 Hz or less, and was considered as a stochastic differential equations.

Key words: Nonlinearity, Bio-Signal, Surrogate Data, Low-Pass Filter, Wayland Algorithm

1. Introduction

In recent years, the burden on experimental subjects has decreased because small size, non-restriction, and non-invasive devices have become available with the development of physical metering equipment. Therefore, complicated measurements, such as the body sway while watching a picture and the muscle potential at the time of exercise, have been enabled. However, noise such as breathing and body movement is not excluded from the measurement because the signal of the living body is feeble. Hence, processing using a low pass filter has been successfully used to address the mixture of noise. However, in noise processing with a low-pass filter, there exists a problem whereby the resulting changes greatly depend on the value of the cut-off frequency. Therefore, it is important to set a cut-off frequency band that is suitable to biological signal analysis targets. Currently, the value of the cut-off frequency is often empirically determined and differs according to the experimenter. Therefore, this study investigated the value of the low pass filter's cut-off frequency, and aimed at objectively evaluating the cut-off frequency by concentrating on the fact that the bio-signal properties change according to the value of the cut-off frequency. The brain activity during biofeedback (BF) and the body sway during stereoscopic image viewing were considered as the bio-signal. The brain activity was measured using near-infrared spectroscopy (NIRS), which can non-invasively measure changes in the cerebral blood flow of living bodies.

Biofeedback (BF) refers to technologies and phenomena that can consciously control some physical activity by feeding back physical activity that cannot be consciously controlled, such as the heartbeat and body temperature. Moreover, BF is often used as a physical process to relieve tension and pain and to promote health. A BF instrument

performs three tasks. First, it monitors (in some capacity) a physiological process of interest. Secondly it measures (quantifies) what is being monitored. Thirdly, it presents what is being monitored or measured as meaningful information. Electromyography (EMG) and BF handle motion during treatment, and are often used concurrently. Additionally, BF training (BFT) does not only refer to techniques that promote health, but is also thought to affect the development and maintenance of brain functioning [1]. In fact, progressive muscle relaxation is used to control anxiety and is thought to promote self-care and enhance overall health [2]. Jacobsen (1938) developed progressive muscle relaxation as an effective behavioral technique for the alleviation of neurotic tensions and many functional medical disorders. He used crude electromyographic equipment to monitor the levels of tension in the muscles of his patients during treatment. The classification of and a historical perspective on biofeedback applications can be found in reports by Gatchel and Price (1979) and Gaarder and Montgomery (1981). Basmajian *et al.* (1989) comprehensively reviewed the applications and historical perspectives of BF, which are beyond the scope of this discussion [3–5]. BFT is not only a technique used for health enhancement, but is also thought to affect the development and maintenance of brain functions [6, 7]. The connection between BFT and brain functions will certainly attract more attention in the future, seeing as current studies have reported that BFT does not only involve the voluntary movement of the extremities and joints, but also receives input from the brain's high-level integrative functions.

Recently, it was shown that the mass of hip flexor muscles, which are used to bend the hip joint when walking, rapidly reduces with age. Hip joint flexors, which include the femoral rectus and abdominal muscles, have been implicated in falling incidents involving elderly people. The blood flow in the cerebrum can easily contain artifacts such

as those produced by physical exercise and cardiovascular activity. Therefore, in this study, the effect of local exercise was evaluated for sitting subjects, and the average rectified EMG of the femoral rectus muscles performed during the BFT of the dominant leg was investigated. BF techniques allow subjects to observe the EMG signals or signal-derived outputs so as to encourage the self-control of a specific muscle. This technique has been used to develop a local exercise technique for muscles, including the femoral rectus, and thus contributed to fall prevention and health enhancement for elderly individuals. Instructions are frequently provided using a visual or auditory signal.

Brain functional imaging using NIRS is a technique that has been developed in recent years and is used for the non-invasive measurement of brain activity. Owing to developments such as the miniaturization of diagnostic equipment, brain science is rapidly being developed and various brain activities are being defined [8–10]. In brain activity measurements using NIRS, the prefrontal cortex (related to the working memory, attention control, cognition, and emotion) and the premotor cortex (related to motion planning and preparation) are activated during low-load full-body movement such as walking [11]. In fact, studies have reported that the cognitive functioning of elderly people improves through walking exercise [12]. Moreover, previous work by the authors has demonstrated that it is possible for specific local movement (masticatory movement in this case) to stimulate activity in the prefrontal cortex [13].

This study used EMG and NIRS simultaneously to make measurements in the femoral rectus of healthy young subjects, whose physiological properties are not markedly different from those of healthy elderly subjects, so as to reveal the effect of BFT on the brain and particularly on the prefrontal cortex. Additionally, the effect of BFT exercise tasks on the local cerebral blood flow was investigated.

2. Material and Methods

Typically, we do not recognize the body regulation with involuntary movement; however, visualization using the electromyogram (EMG) and electrocardiogram (ECG) has revealed teacher signal in the BFT. Apart from mental relaxation training, BFT has also been applied to patients with intractable epilepsy and used for gait training [6, 7]. The objective of the BFT is to recover the functioning of the body.

2.1 Experiment 1

NIRS requires less restraint on the subject compared with other techniques such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) [14–16]. NIRS measures the changes in the concentration of hemoglobin (Hb) in the blood. Although there exists a limitation in the wavelength range at which near infrared light is absorbed into the body [17], near infrared light scattered into the brain tissue from above the scalp can still reach the cerebral cortex [18]. Moreover, the cerebral cortex is located at a depth of 15–20 mm from the scalp and exhibits close correlation between the neural activity and the capillary constriction or dilation. Therefore, the cerebral cortex is suitable for measuring changes in the intracerebral hemoglobin concentration associated with brain activ-

ity. Furthermore, the cerebral cortex is also critically linked to movement, sensation, language, and cognition. During the NIRS for the cerebral cortex, the activity is measured using multichannel reflection measurements from the scalp. Briefly, light-emitting probes and light-receiving probes are placed on the scalp, and then near infrared light (wavelength of 700–900 nm) with high permeability into the bio-tissue is emitted from these light-emitting probes. Then, the light-receiving probes detect light that is scattered and reflected by the cerebral cortex.

Blood contains two types of hemoglobin with different absorption spectra, namely, oxygenated hemoglobin (Oxy-Hb) bound to oxygen and deoxygenated hemoglobin (Deoxy-Hb) that is not bound to oxygen [17]. This study considered this characteristic to measure the Oxy-Hb concentration (Co) and Deoxy-Hb concentration (Cd) using the continuous wave (CW) method, based on the attenuation of detected light versus the intensity of the near infrared light reflection at two wavelengths, namely, λ_1 and λ_2 . The CW method is based on the modified Lambert-Beer (MLB) method and measures the concentration change from the beginning of recording multiplied by the optical path [17, 19]. This method is useful because the human body strongly scatters light, which means that the direct optical path from emission to detection cannot be reliably measured; thus, the obtained values do not represent the absolute Hb levels. Measurements using NIRS assume neurovascular coupling in the same manner as other measuring techniques [19]. Neurovascular coupling in the brain refers to the blood vessels dilating near the active nerves, such that arterial blood containing high levels of oxygen and glucose can be supplied with associated changes in Oxy-Hb and Deoxy-Hb [20]. Additionally, the active states in the brain regions can be estimated by measuring the changes in the cerebral blood flow. In fact, it has been demonstrated that the increase and decrease of localized Hb (Co, Cd) reflect the cerebral activity [21, 22]. Biometric data for the femoral rectus muscle were obtained from ten healthy young individuals (24.7 ± 4.5 years) with no abnormalities in their extremities and without previous medical history of ear or nervous system disease. All subjects were of approximately average size, and their body mass index (BMI) was distributed from 18 to 25 kg/m^2 . The experiment was fully explained to the subjects beforehand, and their written consent was obtained. Additionally, the experiment was approved by the Ethics Committee of the Department of human and artificial intelligent systems, Graduate School of Engineering University of Fukui (No. 2).

Surface EMG tests were carried out by connecting an EMG transformation box (AP-U027, TEAC Co., Tokyo) to a commercially available portable multi-purpose bio-signal amplifier-embedded collection device (Polymate AP1532, TEAC Co., Tokyo) and by using dedicated bipolar EMG electrodes with pre-amps (20 dB). Additionally, AP Monitor (NoruPro, Tokyo), which is a software that simultaneously displays the teacher signal of the BFT and the smoothed EMG sequences for the subjects, was used for recording on a personal computer at a sampling frequency of 2 kHz to show the muscle activity of the subjects in real time. The process was fully explained to the subjects prior

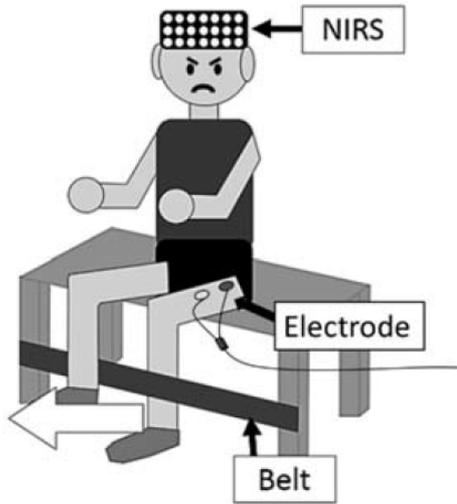


Fig. 1. Biofeedback training experiment for rectus femoris muscle.

to the tests and consent was obtained in writing.

The following outline summarizes the experimental process:

Step 1: The subjects were asked to sit back on a chair (with four fixed legs) and kick with their dominant leg against a belt attached to the lower part of the chair (Fig. 1).

Step 2: Away from the center of the femoral rectus, AMG electrodes were placed at intervals of a few centimeters and the subjects were asked to perform their maximum voluntary contraction. The average integral waveform of the surface EMG was calculated for this period of muscle contraction. Then, the muscular activity corresponding to $\alpha = 75\%$ (third quartile) of the maximum voluntary contraction was estimated.

Step 3: The muscular activity corresponding to $\alpha\%$ of the maximum voluntary contraction was presented to the subject as the instruction signal. Five cycles of intermittent signals were provided for 40 seconds of contraction (gradual build-up during the first 20 seconds), which will hereafter be referred to as the transient period (TP). This was followed by 20 seconds of constant muscle activity, which will hereafter be referred to as the muscle contraction period (MCP). Subsequently, relaxation was allowed for 40 seconds (the first 20 seconds are referred to as pre-rest and the last 20 seconds are referred to as post-rest). This series of flows was carried out five consecutive times (Fig. 2).

The EMG waveforms obtained over 400 seconds were rectified and smoothed in real time at 0.1-second integration intervals. Subsequently, these integral waveforms were shown to the subjects (in addition to the instruction signals). The cut-off frequency for the high and low range cut-off filters was set to 1 kHz and 16 kHz, noise was removed from the surface EMG by inserting an AC removal filter, and evaluation was performed through a sensor output signal evaluation system.

Step 4: In conjunction with Step 3, the optical brain function imaging device LABNIRS (Shimadzu Corporation, Kyoto) was used to measure Co and Cd at a sampling frequency of 17.5 Hz [19, 23]. A holder was placed on

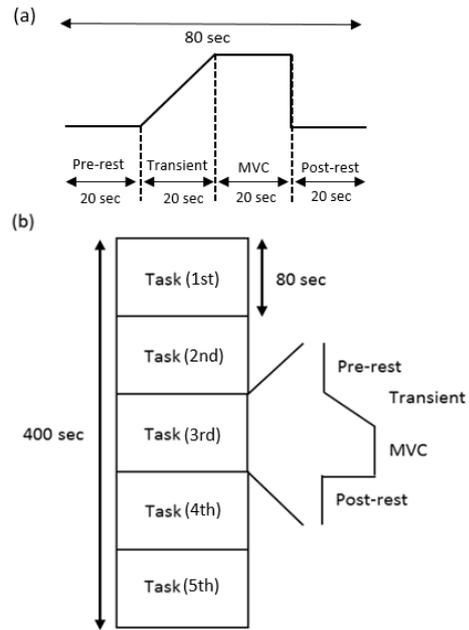


Fig. 2. Experimental protocol: (a) procedure for single task; (b) series of procedures for repeated tasks.



Fig. 3. Array of irradiation and light-receiving probes.

the subject's head, with light-emitting/receiving probes arranged based on the international 10–20 sensor placement, as shown in Fig. 3. The changes in the cerebral blood flow concentrations were measured for the frontal lobe in 54 channels (Fig. 3).

2.2 Experiment 2

Ten healthy male volunteers (mean \pm standard deviation: 22.6 ± 0.8 years) participated in this study. Stabilometry was carried out while viewing stereoscopic video clips with augmented reality (AR) technology. Additionally, in this experiment, fNIRS and ECG were simultaneously measured.

The subjects viewed stereoscopic video clips through the transmission type of the head-mounted display (HMD; MOVERIO BT-200, EPSON, Nagano). The stabilograms were recorded using the Wii Balance Board (Nintendo, Kyoto), and the sampling frequency was set to 100 Hz.

The experiment was conducted in a dark room. The subjects stood on the Wii Balance board in the Romberg posture and wore the transmission type of the HMD. All

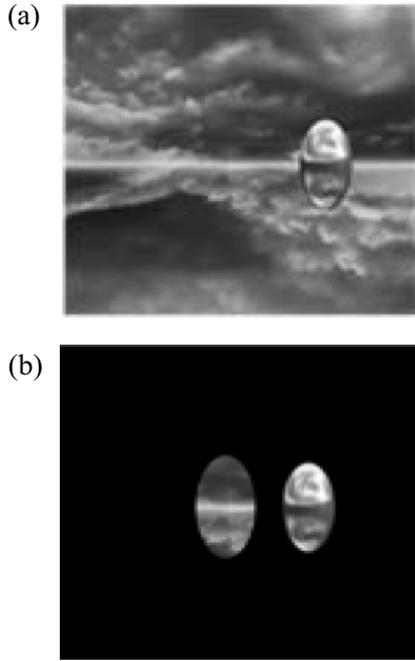


Fig. 4. Video clips: (a) VC1 and (b) VC2.

subjects provided informed consent prior to their participation. The following subjects were excluded from the study: subjects working the night shift, subjects with alcoholism problems, subjects who consumed alcohol and caffeine-containing beverages after waking up and less than 2 h after meals, subjects who had been using prescribed drugs, and subjects who may have previously suffered from otorhinolaryngologic or neurological diseases. This study was approved by the research ethics committee of the Department of Human and Artificial Intelligent Systems, Graduate school of Engineering, University of Fukui (No. 2018010).

In peripheral viewing, stereoscopic video clips were exposed to the subjects (Fig. 4), who viewed the ordinal stereoscopic video clip (VC1) for the first 60 s after the onset of the measurement, then viewed the other video clip (VC2) for the next 60 s while the visual field was constricted, and were at a position of static standing for the last 30 s. In this study, the abovementioned protocol was repeated five times.

3. Analysis

Based on the Fourier-Shuffle surrogate method, we investigated whether the mathematical models describing the cerebral hemodynamics and body sway were nonlinear. Additionally, the time series data were smoothed using low-pass filtering to investigate whether the cut-off frequency in common was suitable for nonlinear analysis. The surrogate sequences were obtained from the inverse transform of the Fourier spectrum, whose phase components were shuffled at random.

3.1 Experiment 1

For each subject, standardization was performed using the average Co in the pre-rest period for each BFT cycle and the standard deviation. Standardized sequences were obtained for the pre-rest, TP, MCP, and post-rest periods.

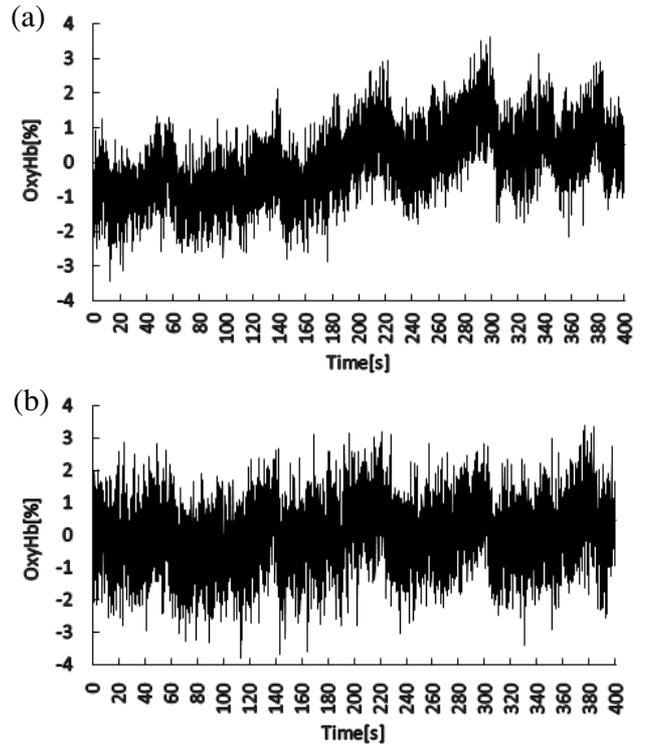


Fig. 5. Standardized variations of local cerebral blood flow: typical graph of time series of Co for (a) 8 ch and (b) 36 ch.

In this study, we analyzed the time sequences of the Co for 8 channels. The time series were smoothed using low-pass filtering, whose cut-off frequency f_0 was set to 0.1, 0.2, 0.3, 0.5, 1, 1.5, and 2 Hz, respectively. Additionally, it was possible to measure the degree of determinism for the mathematical model of the time series $\{x(t)\}$. The translation errors E_{trans} [23] and the sequences of their temporal differences were estimated for each time series using the Double-Wayland algorithm [23, 24]. Additionally, we compared the E_{trans} of the abovementioned time series with their surrogate sequences generated using the Fourier shuffle (FS) algorithm [25, 26]. The length of the time series must be 2^n because this algorithm performs fast Fourier transformation (FFT). In this study, the length of the time sequences was set to 256 ($n = 8$), and the time sequences extracted from the onset time (0 s) to 15 s/6 s to 20 s were defined as the first half period and latter half period, respectively. The value of E_{trans} was estimated as the average of the first half and latter half period values.

These translation errors were compared with each other by carrying out the Welch-Aspin test to evaluate the non-linearity of the mathematical model describing the cerebral hemodynamics. The significance level was set to 0.05.

3.2 Experiment 2

As stated in Subsection 2.2, this protocol was repeated five times; however, the FS method was used in the first experimental period. The time series data for each component were smoothed using low-pass filtering, and their cut-off frequency f_0 was set to 0.1, 0.15, 0.2, 0.3, 0.5, 1, 1.5, 2, 3, 5, 10, 15, and 20 Hz; the translation error was estimated from each set of data.

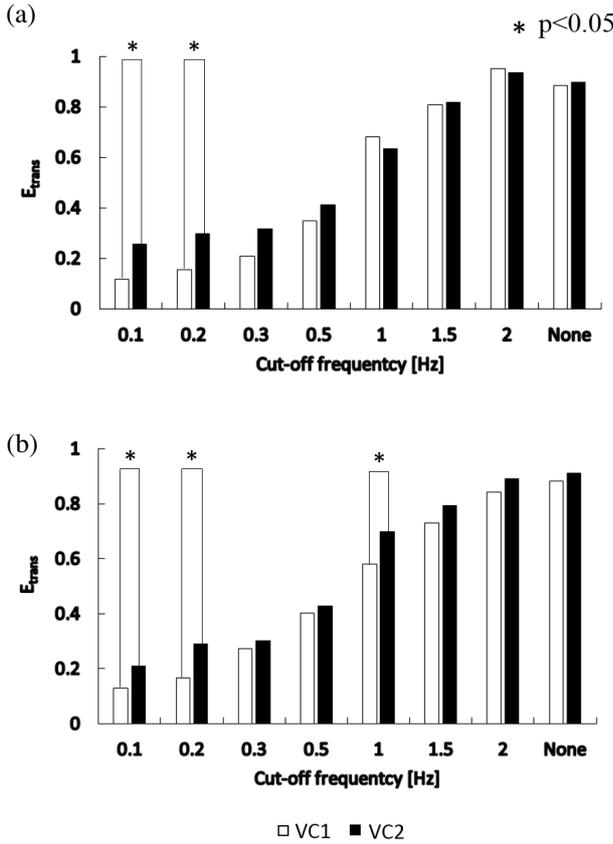


Fig. 6. Statistical comparison between E_{trans} estimated from standardized time series smoothed using low-pass filtering and E_{trans} obtained from surrogate sequences: translation errors E_{trans} for (a) MCP and (b) post-rest periods.

4. Results

4.1 Experiment 1

BFT was carried out for 10 subjects, and the records of the muscle performance in the BFT were confirmed using the sensor output evaluation system. For all subjects, the smoothed integral signal of the rectified EMG was adequately fitted to the teacher signal. Time series data were also recorded for the local cerebral blood flow in the frontal lobe at 54 channels (Fig. 3).

In this study, we focused on the period of the fourth task (Fig. 5a), which is comparatively stable compared with the other periods. Standardized sequences were extracted for the fourth task, as shown in Fig. 5a. Data analysis was conducted and the time series was smoothed using low-pass filtering, whose f_0 was set to 0.1, 0.2, 0.3, 0.5, 1, 1.5, and 2 Hz, respectively. Considering the differences between the time series data, E_{trans} was estimated as $\{x(t + \tau) - x(t)\}$ for the time series data of Co and the sequences of their temporal differences; the delay time τ is the time required until the auto-correlation function of each time series data becomes less than $1/e$ [27]. The growth of E_{trans} monotonically increased according to the increase of the cut-off frequency f_0 for the bounded domain (at least ≤ 2 Hz). Additionally, a gentle decrease was observed without the finite domain. Based on these E_{trans} values for $f_0 \geq 0.2$ Hz, it can be solidly argued that, in the MCP and

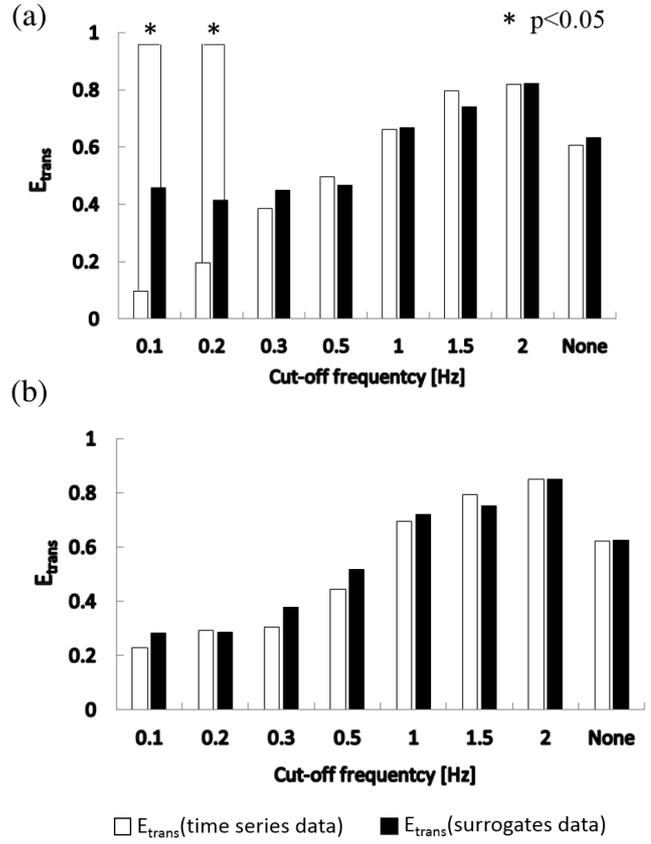


Fig. 7. Statistical comparison between E_{trans} estimated from sequences of temporal differences and E_{trans} obtained from surrogate sequences: translation errors E_{trans} for (a) MCP and (b) post-rest periods.

post-rest periods, the cerebral hemodynamics are described by a stochastic process. The next section discusses this assumption in more detail.

By setting the following statistical hypotheses, E_{trans} was compared with the surrogate sequences of each time series, which were generated by the FS algorithm [27].

Null hypothesis H_0 : the time series are generated by a linear mathematical model.

Alternative hypothesis H_1 : the time series are generated by a non-linear mathematical model.

For the MCP, statistical significances were observed when the translation errors estimated from the standardized time series that was smoothed using low-pass filtering ($f_0 = 0.1, 0.2$) were compared with those obtained from their surrogate sequences, respectively (Fig. 6a). Statistical significances were also observed by comparing the translation errors estimated from the sequences of temporal differences ($f_0 = 0.1, 0.2, 1$) with those obtained from their surrogate time series, respectively (Fig. 7a).

In these cases, the null hypothesis was rejected as shown in Fig. 6 ($p < 0.05$).

For the post-rest period, statistical significances were observed when comparing the translation errors estimated from the standardized time series that was smoothed using low-pass filtering ($f_0 = 0.1, 0.2$) with those obtained from their surrogate sequences, respectively (Fig. 6b). However, statistical significance was not found when comparing the

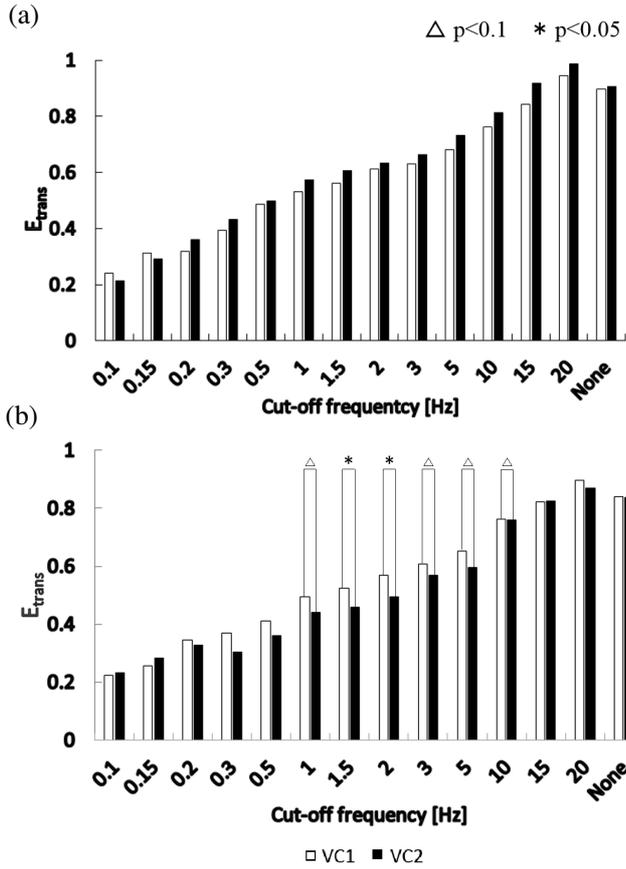


Fig. 8. Lateral translation errors for each stabilogram component while viewing VCs: (a) translation error estimated from time series body sway data and (b) translation error estimated from sequences of their temporal differences.

translation errors estimated from the sequences of temporal differences with those obtained from their surrogate time series (Fig. 7b).

4.2 Experiment 2

The translation errors were estimated from the time series body sway data for the X component (lateral direction) and Y component (anterior/posterior direction) while viewing VC1 and VC2, respectively. Significance was not observed in the translation error values estimated from the time series data. For the lateral direction, by setting the cut-off frequency of the low-pass filtering to 1.5 and 2 Hz, significant differences were observed in the values of the translation error E_{trans} estimated from the differences between the time series data recorded while viewing VC1 and those recorded while viewing VC2 (Fig. 8).

When the cut-off frequency of the low-pass filtering was set to 1–10 Hz, the values of the translation error E_{trans} that were recorded while viewing VC1 tended to be different from those recorded while viewing VC2. However, statistical significance was not found in the anterior/posterior direction.

The translation error values estimated from the surrogate data were compared with those obtained from each stabilogram component while viewing the VCs (Fig. 9).

By setting the cut-off frequency of the low-pass filtering to 0.1–0.5, 5, and 10 Hz, significant differences were

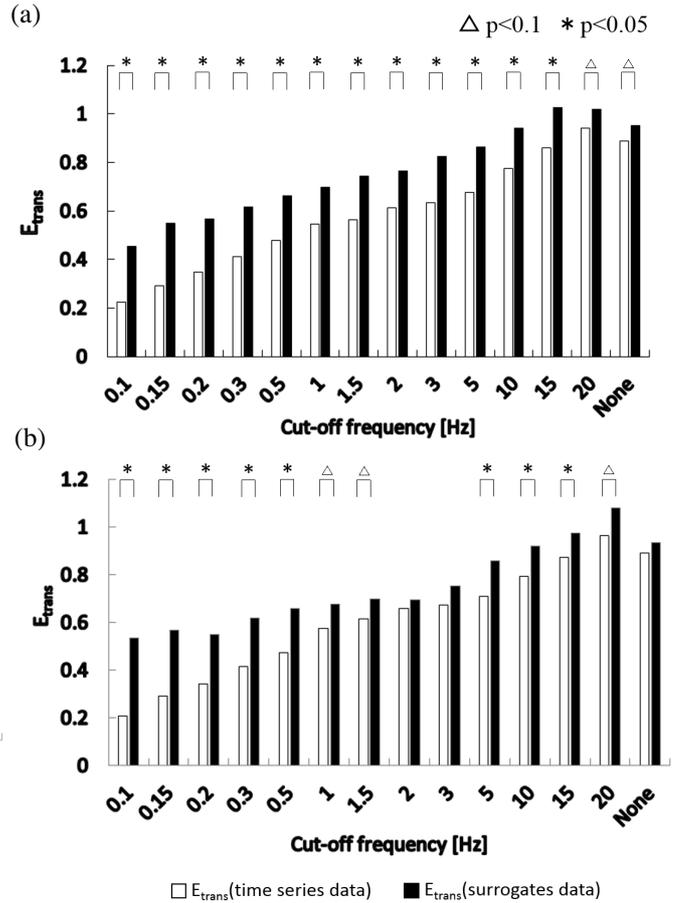


Fig. 9. Lateral translation errors estimated from each stabilogram component and their surrogate data (a) while viewing VC1 and (b) while viewing VC2.

observed between the values of the translation error while viewing VC2. Additionally, by setting the cut-off frequency of the low-pass filtering to 1, 1.5, 10, and 15 Hz, significant differences tended to exist between the translation error values (Fig. 9b). Hence, the nonlinearity of the mathematical body sway model could only be determined if the cut-off frequency was set to the abovementioned condition. Moreover, the nonlinearity of the mathematical model of the body sway while viewing the VC1 (Fig. 9a) could not be found in the results of statistical comparisons while viewing the VC2 (Fig. 9b).

5. Discussion

This study conducted nonlinear analysis for the cerebral hemodynamics and body sway. Additionally, we successfully determined the cut-off frequency of the low-pass filtering, from which the nonlinear stochastic differential equations were obtained as the mathematical models of the abovementioned bio-signals. Generally, the cut-off frequency in common was considered to be suitable for nonlinear analysis.

The BFT is also known as a countermeasure for patients with intractable epilepsy and as a method of reducing mental stress [28, 29]. Although an objective evaluation method has not yet been established, subjective evaluation has been

carried out and the relevant findings have been reported by a previous study. Additionally, the cerebral hemodynamics and the investigation of the cerebral blood flow regulation during the BFT have not been previously evaluated. According to our previous bio-signal consideration, it is necessary to evaluate the robustness of the bio-system using mathematical models because the changes in the system can hardly be detected. Moreover, it is important to set the cut-off frequency and denoise the bio-signal, particularly in brain function analysis. However, the cut-off frequency has not been previously defined based on mathematical considerations. Therefore, this study focused on mathematically designing the cut-off frequency of the low-pass filtering.

To evaluate the degree of determinism for the mathematical model of frontal lobe hemodynamics, the translation errors were estimated for each time series along with their temporal difference sequences by considering the differences between the time series data. The translation errors estimated in the MCP and post-rest periods were less than those in the other experimental periods. Although this was a relative evaluation, the stationarity in the cerebral hemodynamics was confirmed for the MCP and post-rest periods. The BFT may affect the cerebral hemodynamics, particularly in the frontal lobe and prefrontal cortex, wherein the degree of determinism is enhanced by the regularity of this exercise protocol. Hence, it is important to measure/analyze the cerebral hemodynamics during these experimental periods.

Generally, it can be solidly argued that the E_{trans} values are less than 0.1, as estimated from the deterministic process of the numerical solution to the ordinal differential equations for the embedding dimension ≤ 10 dim [30]. In the MCP and post-rest periods, the cerebral hemodynamics were considered as a stochastic process because the E_{trans} values were not less than 0.1, as estimated from the standardized time series that was smoothed using low-pass filtering for $f_0 \geq 0.2$ Hz. However, the E_{trans} values were saturated for the bounded f_0 -value (≥ 0.2 Hz), and decreased without low-pass filtering as $f_0 \rightarrow \infty$. This occurred owing to the existence of rhythmic artifacts such as the cardiovascular bio-signal or body motion within the BFT.

Moreover, the E_{trans} values estimated from the standardized time series that was smoothed by this low-pass filtering were lower than those obtained from the temporal difference sequences. According to the concept of the Double-Wayland algorithm, the stochastic generators enhance the degree of complexity in the temporal difference sequences.

In the standardized time series smoothed by the low-pass filtering ($f_0 < 1$ Hz), the artifacts could be reduced because the growth of E_{trans} monotonically increased according to the increase of the cut-off frequency f_0 . By setting the cut-off frequency in the low-pass filtering to less than 0.2 Hz, the noise reduction was considered to be more effective compared with the rest of the abovementioned cases. However, the cerebral blood flow in the frontal lobe is not always generated through a stochastic process [27].

The nonlinearity of the mathematical cerebral hemodynamics model was investigated. By setting the abovementioned null hypothesis H_0 , the E_{trans} for each time series (including the temporal difference sequences) was com-

pared with their surrogate sequences generated by the FS algorithm (Figs. 7 and 8). For the MCP period, statistical significances were observed by comparing the translation errors estimated from the standardized time series (including the temporal difference sequences) with those obtained from their surrogate sequences ($f_0 = 0.1, 0.2$), as shown in Figs. 7a and 8a. In these cases, the null hypothesis was rejected, and the nonlinearity in the cerebral hemodynamics could be statistically demonstrated for $f_0 < 0.3$. By setting the cut-off frequency of the low-pass filtering to $f_0 \leq 0.2$ Hz in the time series analysis, it was considered that the cerebral blood flow is generated by the nonlinear mathematical model. Based on stochastic theory, a mathematical model can be derived from the set of stochastic differential equations including the nonlinear group only if the cut-off frequency of the low-pass filtering is set to 0.2 Hz in the analysis of the cerebral blood flow hemodynamics.

However, in the post-rest period, common significance was not observed when comparing the temporal difference sequences with those obtained from their surrogate time series for each cut-off frequency (Fig. 8b), because the translation errors estimated from the temporal difference sequences are more sensitive when the complexity is evaluated during the motion process, compared with those obtained from the time series data.

According to the nonlinear analysis of body sway when viewing the video clip while the visual field is constricted, there were no significant changes with regard to the degree of determinism in the mathematical model of the anterior/posterior motion process. However, remarkable changes in the degree of determinism were observed in the mathematical model of the lateral motion process only when the cut-off frequency of the low-pass filtering was set to 1–10 Hz (Fig. 9). Thus, it is considered that the influence of the peripheral viewing on the body can be measured during the lateral motion process. Moreover, in the lateral motion process, when viewing the video clip while the visual field was constricted, nonlinearity was only observed when the cut-off frequency of the low-pass filtering was set to less than 0.5 Hz.

Acknowledgments. This study was supported in part by the Ogawa Science and Technology Foundation, the Japan Society for the Promotion of Science, and Grant-in-Aid for Scientific Research (C) (Grant numbers 17K00715 and 18K11417).

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