Plethysmogram and EEG: Effects of Music and Voice Sound

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Abstract. We studied a relation of chaotic dynamics of finger plethysmogram to complexity of high cerebral center in both theoretical and experimental approaches. We proposed a mathematical model to describe emergence of chaos in finger tip pulse wave, which gave a theoretical prediction indicating increased chaoticity in higher cerebral center leading to an increase of chaos dynamics in plethysmograms. We designed an experiment to observe scalp-EEG and finger plethysmogram using two mental tasks to validate the relationship. We found that scalp-EEG showed an increase of the largest Lyapunov exponents (LLE) during speaking certain voices. Topographical scalp map of LLE showed enhanced arise around occipital and right cerebral area. Whereas there was decreasing tendency during listening music, where LLE scalp map revealed a drop around center cerebral area. The same tendency was found for LLE obtained from finger plethysmograms as ones of EEG under either speaking or listening tasks. The experiment gave results that agreed well with the theoretical relation derived from our proposed model.

Keywords: Chaos, Lyapunov exponent, EEG, plethysmogram, cerebral, speaking, listening.
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INTRODUCTION

In time series of finger plethysmograms, the presence of deterministic chaos has been evidenced in experiments [1]. Recently an extensive investigation has focused on applying changes of deterministic chaos of finger plethysmograms to estimating physiological/physical status [2], to diseases diagnosis, and to evaluations of mental disorder [4, 2]. However the correlations of chaotic dynamics in finger tip pulse wave to cerebral system that is responsible for mental activities is still not clear. In this paper we address this issue from both theoretical and experimental approaches. We proposed a model to explain an emergence of chaotic dynamics in finger plethysmogram under influences of higher cerebral center. Particularly, the model gave a theoretically relationship indicating the increased chaoticity in higher cerebral region leading to an increase of chaoticity in plethysmograms.

In this paper, after a brief description of the model, we designed an experiment to validate the theoretical prediction. This is the first goal. The experiment included

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observations of both scalp EEG (Electroencephalogram) and finger plethysmogram together with chaos analysis of these physiological signals under mental tasks. Further we computed a distribution of the largest Lyapunov exponent (LLE) on scalp-EEG to understand which cerebral area being coherent to finger tip dynamics.

In the other hand, there are widely studies on effects of mental activities such as speaking, singing, listening voices or listening music. Our second goal in this paper is to study the different effects on human status with respect to speaking a certain voices and listening music based on chaos analysis of scalp-EEG and finger tip pulse wave.

The rest of the paper is descriptions of the model and derived relation in sec. II. A description of experiment method and analysis method in Sec. III and IV. We give results in Sec. V. There are discussions and conclusions in Sec VI.

MATHEMATICAL MODEL

To understand the relation of chaos in the plethysmograms to high cerebral center, a mathematical model is proposed by considering a feedback loop and related physiological factors [3]. Regarding the dynamics of finger plethysmogram was approximated proportionally by the artery blood pressure *p*, we focused on pressure *p*. The pressure receptors are the sensors of the system, which senses and transmits neural afferents from pressure to cardio-vascular center. Neural efferents are created and then sent to effectors. Importantly, there are influences both from a higher cerebral region. Concretely in the model, baroreceptor activity is determined by pressure *p* and its derivative,

$$v_b = k_1\left(p - p^{(0)}\right) + k_2 \frac{dp}{dt} \tag{1}$$

The neural efferent of sympathetic activity is determined by (1) as

$$v_s = \max(0, v_s^{(0)} - k_s^b v_b + k^r(1-\cos(2\pi r)) + \gamma Y) \tag{2}$$

Y is the impulse input from higher cerebral center and is assumed to only affect sympathetic neural efferents through a coupling coefficient γ. *r* is an instance phase of respiration describing effects of respiration modulations. Likewise, efferent parasympathetic activity is determined by equation (1) as

(3)

The instance respiration phase *r* has a constant phase velocity during inspiration.

Pulsating heartbeat is generated by an integrate-and-firing model. A pacemaker phase of sinus node was introduced. A new heartbeat is generated when the phase reaches a threshold of 1.0. At this point the phase is then reset to zero. The phase velocity is determined by sympathetic influence f_s and parasympathetic influence f_p on sinus node according to equation:

$$\frac{d\phi}{dt} = \frac{1}{T^{(0)}} f_s f_p \tag{4}$$

Blood pressure during systolic part of heart cycle is determined by diastolic pressure of previous beat d_{i-1} and cardiac contractility S_i of current beat as:

$$p = d_{i-1} + S_i \frac{t - t_i}{\tau_{sys}} \exp\left\{1 - \frac{t - t_i}{\tau_{sys}}\right\} \tag{5}$$

where t_i is the time at end of last contraction onset.

Cardiac contractility S_i follows Frank-Starling law.

Blood pressure during diastolic part of heart cycle, following a relaxation relation of Windless arteries with a relaxation constant, it is described as

$$\frac{dp}{dt} = -\frac{p}{\tau_v(t)} \tag{6}$$

Since higher cerebral activity played important role in modulation central neural system (CNS) and autonomic system, our model added its influence to sympathetic neural efferent activity through a coupling coefficient γ as shown in equation (2). Dynamics of the cerebral activity was assumed to be described by Duffing equation that was able to generate both limit cycle and chaotic behaviour [5] under different control parameters, as evidenced experimentally by measurements of electroencephalography (EEG). Thus, we chose Duffing equation to describe cerebral impulse activities Y as:

$$\frac{d^2Y}{dt^2} + \varepsilon\frac{dY}{dt} + aY + bY^3 = B\cos\omega t \tag{7}$$

Putting setting of parameters gives arise of chaotic dynamics in agreement with studies on human brain.

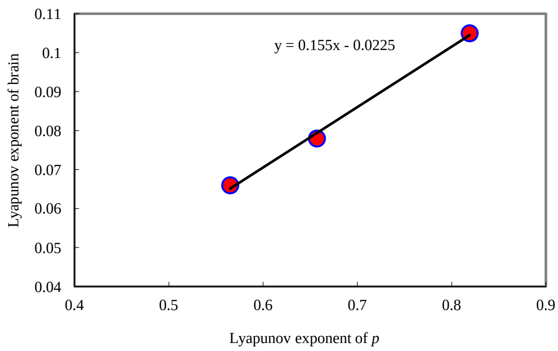

FIGURE 1. Relation of Lyapunov exponents of blood pressure and higher cerebral center.

In simulation studies on the model, we used a Runge-Kutta method to make numerical simulations of the delay-differential equations. Since the dynamics of finger plethysmogram was approximated proportionally by artery blood pressure *p*, we focus only on simulation results on pressure *p*. We obtained time series of blood pressure *p*, which gives analysis of the largest Lyapunov exponent (LLE) corresponding to finger plethysmogram.

Chaoticity in higher cerebral center was described by LLE obtained from chaos solutions of equation (7). Fig.1 plotted the simulated result showing a well linear relationship between LLE in higher cerebral center to ones of finger plethysmogram (blood pressure *p*). This relation implies enhance of chaoticity in higher cerebral center causes an increase of LLE in finger plethysmogram. In other words, there is higher information processing in central neural system, leading to increasing complexity of finger plethysmogram.

In the next section, we designed an experiment to validate the theoretical prediction.

EXPERIMENT METHOD

We had subjects, healthy female from the Holistic Health Science Institute, Kanazawa, Japan. All subjects were informed of the purpose and procedures of the study and signed an informed consent. As shown in Fig.2 of experiment setup, subjects were seated comfortably in a chair in all of experiments conducted by two tasks.

Task 1 is a speaking task. After having a brief rest, subjects were instructed to speaking certain of six voices consecutively, continuously, and naturally. The vocal sound consists of six syllables of Japanese vowels /a/, /o/, /u/, /e/, and /i/n/.

Task 2 is a listening task. Subjects were instructed to listening classic music for a period of time. The music was taken from Mozart collections having slowly and peaceful melodies.

Each experiment had 2min rest and following 2min task. Before and during the tasks, physiological changes were measured by finger plethysmography and scalp-EEG recorder. The plethysmogram was recorded by a device (BACS Advance, CCI 2002) consisting of a sensor attached to a right index finger. The scalp-EEG was recorded using a multi-channel EEG recorder (Neurofax EEG-1200, Nihon Kohden) with 14 active electrodes (Fp1, Fp2, C3, C4, A1 A2, P3, P4, Fz, Cz, Pz). The EEG electrodes were installed according to internal standard (10/20) as shown in left of Fig.2. All signals were A/D digitized and converted into a PC for analysis with sampling frequency of 200Hz for finger plethysmogram and 500Hz for scalp EEG.

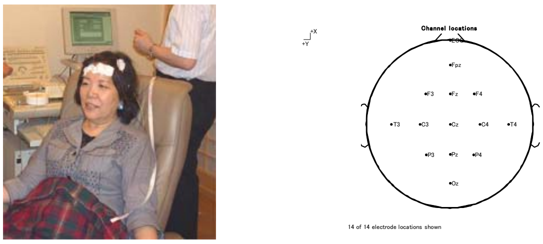

FIGURE 2. Experimental setup (Right) and scalp electrode map (Left).

ANALYSIS METHOD

In chaos analysis of short data in order to trace temporal variations, we estimated maximum finite time Lyapunov exponent that may be biased by time-series length. To overcome the drawbacks, we estimated the largest Lyapunov exponent using improved Rosenstein algorithm being able to compute Lyapunov exponent in short and noise data [10]. In this method, with τ time delay and d the embedding dimension, and $x_k(i) = x(i-(k-1)\tau)$ with k=1,..., d, the phase space was reconstructed using time delay coordinate as,

$$\mathbf{x}(i) = (x(i), \ldots,\ x(i-(d-1)\tau)) = \{x_k(i)\} \tag{8}$$

Based on false nearest neighbor analysis, embedding dimension of d=4 and 6 was used respectively, for time series of finger plethysmograms and scalp-EEG. Time delay τ was determined using the first minimum of average mutual information function [6].

From the constructed attractor in phase space, Euclidean distances between neighboring trajectories in state space were calculated as a function of time and averaged over all original nearest neighbor pairs to obtain the average logarithmic rate of divergence:

$$y(i) = \frac{1}{\Delta t} < ln\ (d_j(i)) > \qquad (9)$$

where $d_j(i)$ represents the Euclidean distance between j-th pair of nearest neighbors after i discrete time steps. and $< - >$ denote the average over all values of j. The slope of the resulting divergence curves provides an estimate of LLE. Further, Liu [9, 10] improved the calculation including nonlinear regression to the divergence curves, giving a robust computation in dealing with short and noise data. In our computations, among both the rest and task periods, time length of 8s and 14s was used for analysis of EEG and plethysmograms, respectively.

RESULTS

Result of chaos analysis of scalp-EEG

Fig.3 shows the largest Lyapunov exponent (LLE) estimated for scalp EEG before and during Task 1 (speaking task), with respect with subject 1(a) and subject 2(b). As shown in above part in Fig.3, most of channels (ordered 1-14) show an increase tendency of LLE during Speaking Task in comparison with Before (rest period). Topographical 2-D scalp map in Fig.3 is a distribution of LLE on cerebral scalp map. Especially LLE around occipital and right cerebral area reveal enhanced increase during Speaking. Frontier cerebral area shows small or little changes.

(a) Subject 1 (b) Subject 2

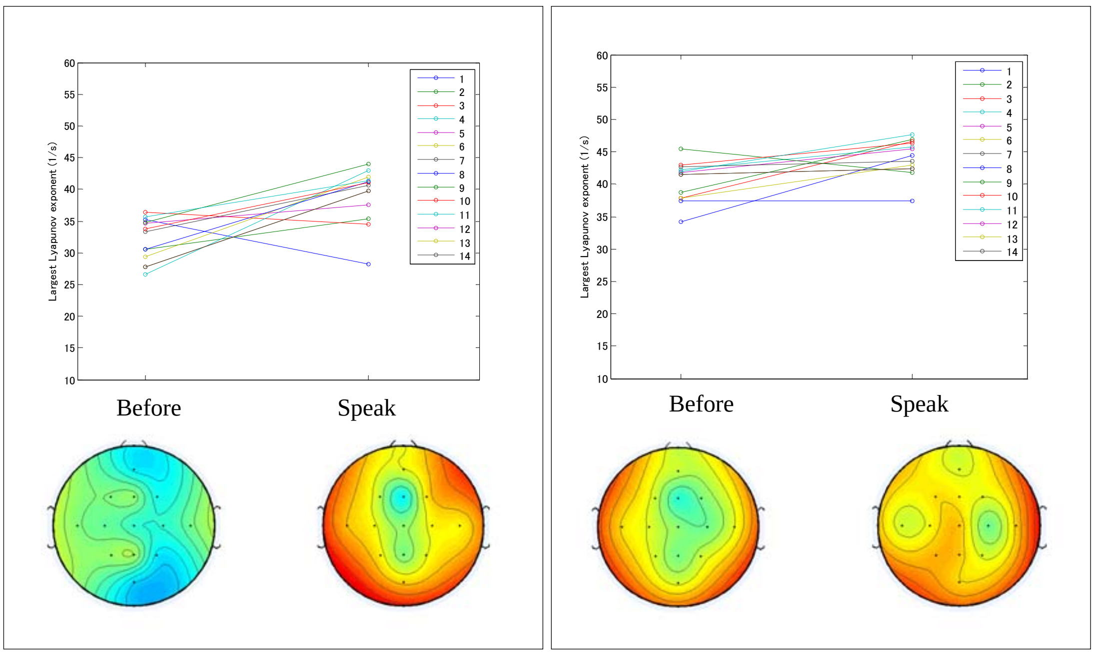

FIGURE 3. LLE of scalp-EEG before and during Speaking for subject 1(a) and 2(b). Scalp map is a distribution of LLE on brain scalp.

Fig.4 shows LLE estimated for scalp EEG before and during Task 2 (listening music task) for subject 1(a) and subject 2(b). As shown in above part in Fig.3, there is a decreasing tendency of LLE during Listening Task in comparison with Before (rest period). Topographical 2-D scalp map of distribution of LLE show a drop around center cerebral area.

(a) Subject 1 (b) Subject 2

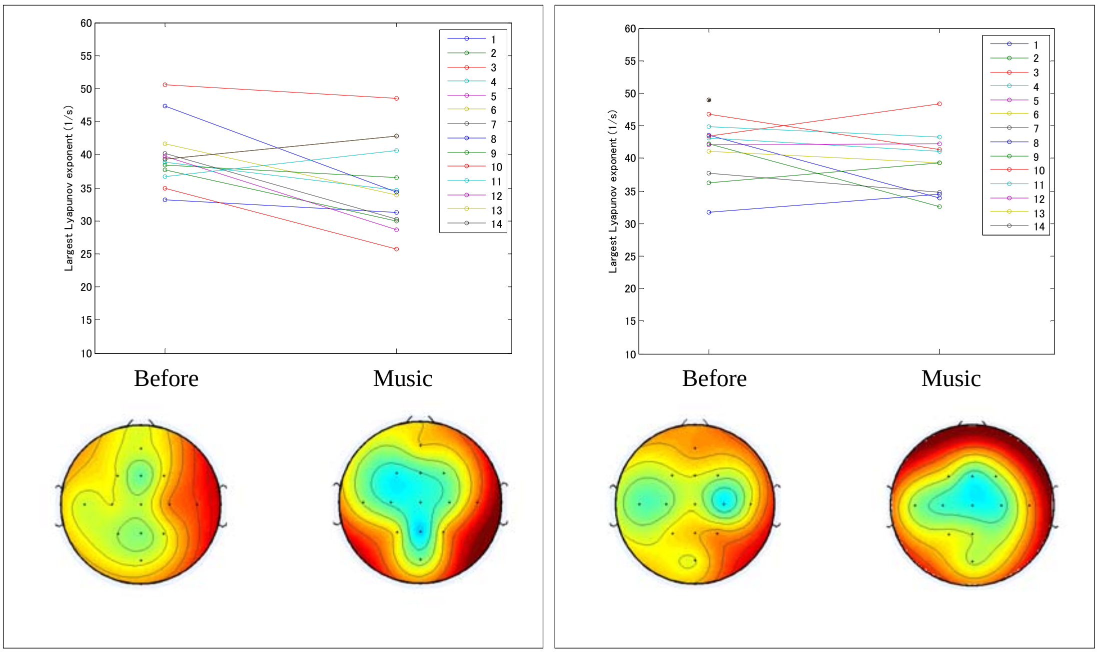

FIGURE 4. LLE of scalp-EEG before and during Listening music for subject 1(a) and 2(b). Scalp map is a distribution of LLE on brain scalp.

Result of chaos analysis of plethysmogram

LLE obtained based analysis of finger plethysmogram are shown in Fig.5 under Task 1 (Speaking) in left and Task 2 (Listening music) in right. Both subjects indicate increasing values during Task 1 (Speaking). Whereas, there is decreasing LLE during Task 2 (Listening).

Finally, in comparison of Fig.5 (Left) with Fig.3, it is clear that the increasing LLE of plethysmogram correspond the same increasing tendency for ones of EEG during Speaking Task. Similarly, there is the same decrease in LLE for both plethysmogram and EEG during Listening Task when comparison of Fig.5 (Right) with Fig.4. These agree well with the theoretical relation obtained from model, as indicated in Fig.1.

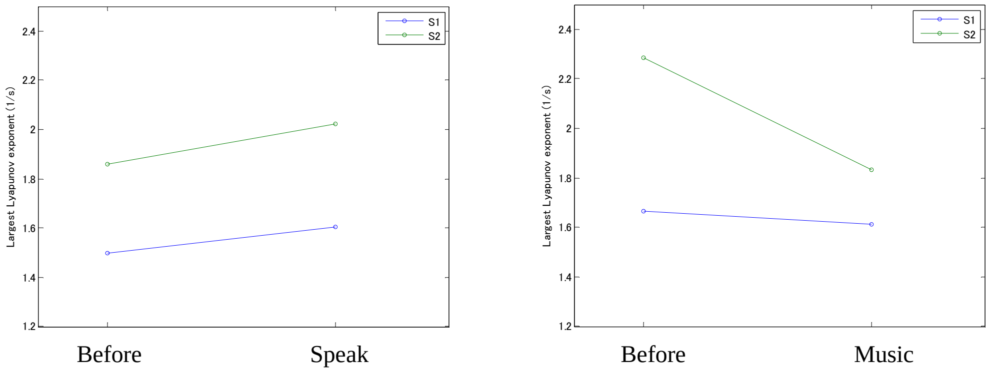

FIGURE 5. Results f finger plethysmogram in experiments conducted by speaking Task (Left) and Listening Task (Right).

DISCUSSION AND CONCLUSION

We studied the relation of chaotic dynamics of finger tip pulse wave to cerebral system that is responsible for various mental activities from both theoretical and experimental approaches. In our model, we give a theoretical relationship indicating the increased chaoticity in higher cerebral region leading to an increase of LLE in plethysmograms.

This paper has two purposes. One is to validate the theoretical prediction, since it is important for guiding practical applications in uses of easily installed finger plethysmogram. Also understanding of this relation may give an insight into the interactions between cerebral system and peripheral arterial system. The second purpose is to study the different effects on physical/mental status due to speaking and listening. We hence designed an experiment to observe both scalp-EEG and finger plethysmograms under tasks of speaking certain six voices and listening classic music. The use of scalp-EEG is to open a possible investigation on which cerebral area being more correlated with finger tip dynamics.

We found that scalp-EEG showed an increase of LLE during Speaking Task in comparison with Before (rest period). Topographical scalp map showed that LLE around occipital and right cerebral area had a largely increase during Speaking. Changes in frontier cerebral area were small. In Task 2, scalp-EEG showed decreasing tendency of LLE during Listening Task in comparison with Before (rest period). Topographical scalp map of LLE revealed a drop around center cerebral area. As illustrated in analysis of finger plethysmogram, it is clear that the increasing LLE of plethysmogram correspond the same increasing tendency for ones of EEG during Speaking Task. Similarly, there is the same decrease in LLE for both plethysmogram and EEG during Listening Task.

In conclude the correlations of scalp-EEG and plethysmogram obtained from experiments showed well agreement with the theoretical relation predicted by our mathematical model. LLE for both EEG and plethysmogram increased due to speaking and decreased in listening.

In future work, we should perform studies for increasing subjects over a variety of tasks and conditions. A detailed analysis is necessary to study underlying mechanism of correlations of scalp-EEG map and finger tip dynamics.

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