Chaos and Nonlinear Time-series Analysis of Finger Pulse Waves for Depression Detection

Tuan D. Pham[1], Truong Cong Thang[2], Mayumi Oyama-Higa[3], Hoc X. Nguyen[2], Hameed Saji[4] and Masahide Sugiyama[2]

[1]*Aizu Research Cluster for Medical Engineering and Informatics, CAIST, The University of Aizu, Aizuwakamatsu, Fukushima 965-8580, Japan*

[2]*School of Computer Science and Engineering, The University of Aizu, Aizuwakamatsu, Fukushima 965-8580, Japan*

[3]*Chaos Technology Research Laboratory, 5-26-5 Seta, Otsu-shi, Shiga 520-2134, Japan*

[4]*Aizu Research Cluster for Environmental Informatics, CAIST, The University of Aizu, Aizuwakamatsu, Fukushima 965-8580, Japan*

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Abstract: Depressive disorders are mental illnesses that can severely affect one's health and well-being. If depression is not early detected and left untreated, it can consequently lead to suicide. This paper presents for the first time a novel combination of chaos theory and nonlinear dynamical analysis of signal complexity of photoplethysmography waveforms for detection of depression. Experimental results obtained from the analysis of mentally disordered and control subjects suggest the potential application of the proposed approach.

1 INTRODUCTION

It has been known that depression has been a highly prevalent, worldwide problem with multiple social and health consequences (Waza et al, 1999). Sad feeling, emotional indifference, and lack of interest reduce one's ability to meet responsibilities and to enjoy life. The causes of depression are complex resulting in biological, psychological, and social dysfunctions or a combination of these problems. Although depression is the frequent mental disorder among older people, its adverse impact on young people is much greater than the elderly. The effects of depression are not limited to a depressed person but they can be far-reaching. Needless to say, the treatment for depression is essential, because the consequences of untreated depression may be fatal.

The literature on improving detection of these issues in primary care settings has predominantly focused on physician skills in assessing mental health problems. While physician factors undoubtedly play a role, it is believed that the detection of mental health problems has not been widely investigated (Marcus et al., 2011). Regarding the computerized detection of depression, photoplethysmography (Allen, 2007) has recently been realized as a useful biomedical technology for studying mental disorders (Hu et al., 2011). While speech (Low et al., 2011), image (Cohn et al., 2009; Soennesyn, et al.), and other biosignals (Chen et al., 2011; Kemp et al., 2012) have been used for depression detection; photoplethysmography waveforms, which are generated from the measurements of blood volume changes in the microvascular bed of tissue at the skin surface and found as effective as ECG (electrocardiography) in measuring the parameters of heart rate variability (Russoniello et al., 2010), provide simple and low-cost optical data for the same study. For the first time, this paper presents the combination of extractions of the Lyapunov exponents and sample entropy values of the photoplethysmography waveforms measured at the finger tips for depression detection.

2 LYAPUNOV EXPONENTS FOR DISCRETE-TIME SYSTEMS

A Lyapunov exponent is a real number that measures the average rate of divergence or convergence over the entire attractor which is the phase-space point or set of points representing various possible steady state of

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a dynamical system (Williams, 1997; Sprott, 2003). For a discrete system, we consider how a 1-D map $x_{k+1} = f(x_k)$ evolves when it is started at two initial states x_0 and $(x_0 + \varepsilon_0)$, where ε_0 is a very small value to indicate the two initial states are very close to each other. The Lyapunov exponent is defined when the two trajectories are separated by a distance ε_n after n iterations of the map as

$$|\varepsilon_n| \approx |\varepsilon_0|^{n\lambda} \tag{1}$$

where λ is the Lyapunov exponent.

Taking the natural logarithm of both sides of Equation (1), the divergence of the two trajectories can be approximated as (Dingwell, 2006)

$$\begin{aligned} \lambda &\approx \frac{1}{n}\left|\frac{\varepsilon_n}{\varepsilon_0}\right| \\ &= \frac{1}{n}\ln\left|\frac{f^n(x_0+\varepsilon_0) - f^n(x_0)}{\varepsilon_0}\right| \end{aligned} \tag{2}$$

If the interest is the study of the effects of very small perturbations, the limit of Equation (2) is taken as $\varepsilon_0 \to 0$, then the remaining term inside the logarithm is expanded using the chain rule:

$$\begin{aligned} f^n(x_0+\varepsilon_0) - f^n(x_0) &= (f^n)'(x_0) \\ &= \prod_{i=0}^{n-1} f'(x_i) \end{aligned} \tag{3}$$

The back substitution of Equation (3) into Equation (2) gives

$$\lambda \approx \frac{1}{n}\sum_{i=0}^{n-1} \ln|f'(x_i)| \tag{4}$$

Finally, the limit of Equation (4) is taken as $n \to \infty$, giving

$$\lambda = \lim_{n\to\infty}\left[\frac{1}{n}\sum_{i=0}^{n-1} \ln|f'(x_i)|\right] \tag{5}$$

For M-dimensional mappings, Equation (5) is extended to yield a spectrum of Lyapunov exponents arranged in a decreasing order:

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_M,$$

where λ_1 is known as the maximum or largest Lyapunov exponent (LLE).

3 SAMPLE ENTROPY

Let $\mathbf{x} = \{x_1, \ldots, x_N\}$, and Q_m be the set of all subsequences of length m in $\mathbf{x}$: $Q_m = \{\mathbf{x}_{1m}, \ldots, \mathbf{x}_{(N-m+1)m}\}$, where $\mathbf{x}_{im} = \{x_i, \ldots, x_{i+m-1}\}$. It is said that $\mathbf{x}_{im}$ and $\mathbf{x}_{jm}$ are similar if and only if

$$|x_{i+k} - x_{j+k}| < r, \forall k, 0 \leq k < m, i \neq j \tag{6}$$

Let $L_m = \{\mathbf{x}_{1m}, \ldots, \mathbf{x}_{(N-m-1)m}\}$, the probability of patterns of length m that are similar to the pattern of the same length that begins at i is

$$B_{im}(r) = \frac{J_{im}(r)}{N-m-1} \tag{7}$$

where $J_{im}(r)$ is the number of subsequences in L_m that are similar to $\mathbf{x}_{im}$.

The total average probability $B_{im}(r)$ for all i, $i = 1, \ldots, N-m$, is

$$B_m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_{im}(r) \tag{8}$$

Finally, the value of SampEn, given m and r, can be calculated by the following equation:

$$SampEn(m,r) = \log\left[\frac{B_m(r)}{B_{m+1}(r)}\right] \tag{9}$$

4 EXPERIMENT

We are interested in applying chaos and nonlinear time-series analysis of finger pulse waves for depression detection by extracting the biosignal features using LLE and SampEn. The experimental data used in this study is the same data recently studied by (Hu et al., 2011). The dataset consists of 195 patients diagnosed with depression and 113 students considered as the control subjects. Finger pulse waves were measured on the depressed and control subjects at various number of times.

The first step in the estimate of the LLE of the finger pulse waves is the reconstruction of an appropriate state space for the nonlinear system. Takens' embedding theory, which states that an appropriate state space from a single original time series can be reconstructed with a time delay (Takens, 1981), is applied here for the state-space reconstruction. The purpose of selecting a time delay is to find a value of the delay which is large enough to ensure that the resulting individual coordinates are relatively independent; however, it should not be so large to be completely independent statistically (Abarbanel, 1996). In this study, the embedding dimensions of the finger pulse waves were chosen to be 4 for the reconstruction of the state space. Because of the difficulty in the computation of the Lyapunov spectrum and the interest in estimating λ_1 (LLE) which is the most significant indicator of chaos, many algorithms have been devoted to the calculation of the LLE. One of the most popular methods for the LLE estimate is the one proposed by Rosenstein et al (1993) and applied in this study.

For the calculation of SampEn, $m = 7$ and $r = 0.2\sigma$, where σ is the standard deviation of the signals, were specified.

Sensitivity and specificity are statistical measures of the performance of a binary classification test. Sensitivity is the measure the proportion of actual positives which are correctly identified as such. In this study, it is the percentage of the depressed patients who are correctly identified as having depression. Specificity is the measure of the proportion of negatives which are correctly identified. Here it is the percentage of the control subjects who are correctly identified as not having depression.

The concept of autonomic nerve balance (Wilson, 2005) stems from the fact that the human nervous system has two major parts: the voluntary and the autonomic systems. The voluntary system is concerned with movement and sensation and consists of motor and sensory nerves.

The autonomic system regulates biological functions such as blood pressure and heart rate over which human beings have less conscious control. The autonomic system has two states: sympathetic (stress) and parasympathetic (healing). Computation of the autonomic nerve balance (ANB), which is based on heart rate per unit time measured from the end pulse wave , was patented and described in (Higa, 2011).

Figure 1 shows the LLE and autonomic nerve balance (ANB) features extracted from the finger pulse waves of the patients and control subjects, and the graphical results obtained by the fuzzy c-means (FCM) clustering algorithm. Figure 2 shows the LLE and SampEn features extracted from the finger pulse waves of the patients and control subjects, and the graphical results obtained by the FCM algorithm. It can be observed from the figures that the distributions of the LLE and SampEn representing the depression and control groups are presented in much more compact and well defined clusters than those of the LLE and ANB. The k-nearest neighbor (k-NN) algorithm, where $k = 7$, was also used to classify the depressed and control subjects in the experiment.

The specificity and sensitivity results provided by the FCM and k-NN using LLE and ANB are shown in Table 1, and the specificity and sensitivity results provided by the FCM and k-NN using LLE and SampEn are shown in Table 2. Based on the results shown in Table 1 and Table 2, the FCM performs better than the k-NN in classifying the depressed patients (sensitivity), but the k-NN gives better results in detecting the control subjects (specificity) than the FCM. For practical purpose, the FCM would be preferred to the k-NN because of the importance of the correct detection of depression. In general, these results show the superior performance for depression detection of the combination of the LLE and SampEn values using either the FCM or k-NN classifier.

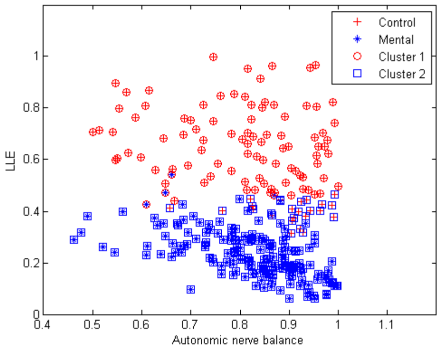

Figure 1: LLE and ANB features of finger pulse waves classified by FCM.

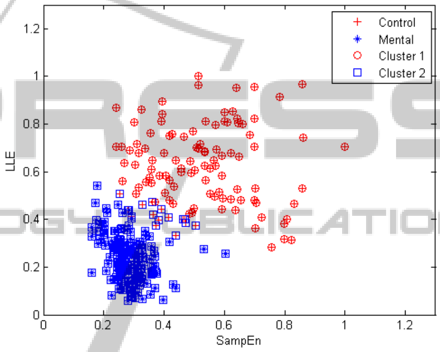

Figure 2: LLE and SampEn features of finger pulse waves classified by FCM.

Table 1: Sensitivity (%) and specificity (%) of depression detection by LLE and ANB.

Classifier	Sensitivity	Specificity
FCM	97.78	79.31
k-NN	92.24	94.44

Table 2: Sensitivity (%) and specificity (%) of depression detection by LLE and SampEn.

Classifier	Sensitivity	Specificity
FCM	1.00	87.07
k-NN	98.89	98.28

5 CONCLUSIONS

The extractions of the finger pulse waves using the largest Lyapunov exponents and the sample entropy values have shown to be a better combination of the biosignal features than the coupling of the largest Lyapunov exponents and autonomic nerve balance values. The improvement suggests the usefulness of chaos and nonlinear dynamical analysis of the photoplethysmography waveforms for depression detection, which can be useful for mental health care.

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