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Wearable Mental-health Monitoring Platform with Independent Component Analysis and Nonlinear Chaotic Analysis

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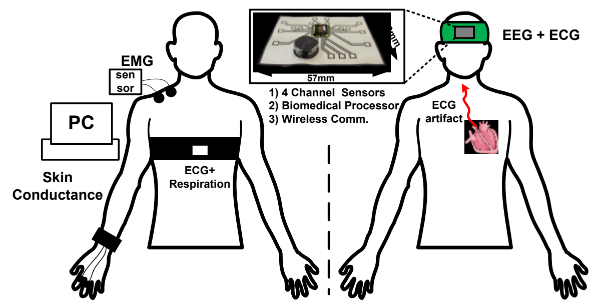
Abstract— **The wearable mental-health monitoring platform is proposed for mobile mental healthcare system. The platform is headband type of 50g and consumes 1.1mW. For the mental health monitoring two specific functions (independent component analysis (ICA) and nonlinear chaotic analysis (NCA)) are implemented into CMOS integrated circuits. ICA extracts heart rate variability (HRV) from EEG, and then NCA extracts the largest lyapunov exponent (LLE) as physiological marker to identify mental stress and states. The extracted HRV is only 1.84% different from the HRV obtained by simple ECG measurement system. With the help of EEG signals, the proposed headband mental monitoring system shows 90% confidence level in stress test, which is better than the test results of only HRV.**

I. Introduction

According to the report of Centers for Disease Control and Prevention [1], mental illnesses account for a larger proportion of disability in developed countries than any other group of illnesses, including cancer and heart disease. Especially, mood anxiety, or depression, is one of the frequently occurring illnesses in the mental health. The increasing number of depressed patients is one of the world wide social problems [2]. For the efficient treatment of the mental illness caused by mental and emotional stress, early diagnosis is required.

As people get mental and emotional stress, the organs of human body are affected by nervous system and hormonal control. With acquisition of these changes, the mental stress detection has been researched [3]. Essentially, the main reaction to human emotion occurs in the brain. The brain is the organ which controls human mental as well as human nervous system. Therefore, the detection of brain signals is also the important parameter to determine the mental status. In this research, both EEG signal, which is one of the brain signals, and heart rate variability (HRV), which is the representative variation of organs, are used.

Previously, in order to remove the artifact and noise contaminating EEG signals, independent component analysis (ICA) was adopted in [4]. Most applications of ICA have focused on removal of artifact from EEG signals. Now, in this research, ICA is used not only to remove the artifacts but also to reuse the artifact to extract feature. The removed ECG artifact component is extracted to heart rhythm. In addition to ICA, so as to analyze EEG signals, which is the complex combination from neurons, the nonlinear chaotic analysis (NCA) is adopted instead of the linear method. NCA helps to extract the nonlinear markers while the classical linear method cannot extract them [5]. Due to the requirement a lot of computation power for ICA and NCA, with implementation of application specific integrated circuits (ASIC), low-power and wearable system is realized [6].



EMBC ' 11 [3]		Proposed
3 pieces	Size	1 piece
Disabled hand	Mobility	free hands
Hard to use outside	Wearability	Anywhere wearable
ECG, EMG, SC, Resp.	Signals	EEG, ECG

Figure 1 Application of the proposed system

In this paper, a headband mental-health monitoring system will be proposed using EEG and HRV signals as shown in Figure 1. This system makes people see and record their mental state and raw signals from the brain. The recorded database can be transmitted to experts such as psychiatrists for diagnosis. The previously reported method in [3] has limitation on implementation of mobile device. 1) The sensor system requires large size to cover all of the signals. 2) During the measurement period, movement is limited because of skin conductance (SC) sensor. 3) The chest band and SC sensor decrease wearabillity. The proposed system consists of only the headband so that it is possible to move arms during the measurement. In addition, easiness of wearing results in that it is able to be used in anywhere and anytime user wants.

The rest of this paper is organized as follows. In section II, the analysis method of measured signals will be introduced. Then, the measurement and analysis results are shown in section III. After that, the implemented system is described in section IV. Finally, the conclusions will be made in section V.

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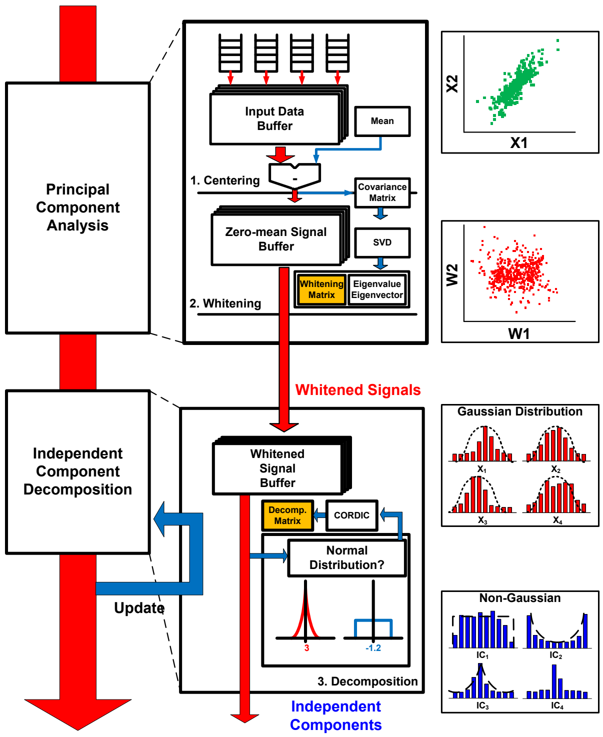

Figure 2 Implementation of ICA

II. Method

A. Independent Component Analysis (ICA)

Since the scalp EEG is polluted by noise and artifacts such as eye movement, patient's movement and heartbeat in general, the measured signals from the scalp are combination of brain active potentials and other artifacts passing through soft tissue and bone. Mathematically, it can be represented as

$$x(t) = A \cdot s(t) \tag{1}$$

where *x(t)* is measured signal at time *t*, *A* is mixing matrix through tissues and bone and *s(t)* is inferred original signals. For the sake of analyzing the behavior of brain more accurately, the original signals should be acquired. ICA is the original source inferring method which calculates and infers the original sources from the measured EEG signals. ICA is able to separate original signals based on the central limit theorem and assumption that original signals are statistically independent. By centrum limit theorem, the measured signals outside the brain have Gaussian distribution even though they are combination of independent sources.

The calculation of ICA can be explained into two steps: principal component analysis (PCA) and independent component decomposition. The first step is PCA, which separates the measured signals into the uncorrelated signals as pre-processing step. Figure 2 describes the signals flow of PCA for the measured signals in the ASIC. First, the measured signals are stored in the temporal buffers. Subtracted by mean values, the zero-mean signals generate covariance matrix, which shows the correlation of the zero-mean signals. Mathematically, with eigenvalues and eigenvectors of the covariance matrix, the zero-mean signals can be transformed to whitened signals, as the covariance matrix becomes identity matrix. As a result of PCA, the whitened signals can be obtained, but they have limitation because the axis of the distribution is fixed to right angle in PCA operation. After PCA, the independent component decomposition occurs to remove their Gaussian distribution. In this step, the whitened signals are decomposed with decomposition matrix. In the early trials of updating, the decomposed independent component (IC) is not perfectly independent. The functions such as Kurtosis indicate whether the signal distribution is Gaussian distribution or not. The decomposition matrix has been updated for the signal distribution to become non-Gaussian distribution. If those signals are uncorrelated and have non-Gaussian distribution, we can call them statistically independent.

By applying ICA to the measured signals, noise-free EEG signals as well as noisy ECG signal can be achieved. With the peak detection algorithm, ECG signals can be transformed into HRV. HRV has several markers such as mean and standard variation and low frequency (0.04-0.14Hz) and high frequency (0.15-0.4Hz) power.

B. Nonlinear Chaotic Analysis (NCA)

Since the brain consists of many neurons and neural network. The EEG signals, generated from the neural network, have nonlinear behavior so called chaotic behavior. Nonlinear analysis can be applied to evaluate the dynamics of neural signals. While classical linear analysis is used widely for signal analysis, nonlinear analysis can extract the feature which the linear method cannot quantify.

In order to calculate nonlinear chaotic index such as largest Lyapunov exponent (LLE), correlation dimension (CD) and entropy, the construction of the phase space is required. If the time-series signals are generated to be analyzed like the signals shown in the Figure 3 (a), the phase space, called as attractor, is constructed in n-dimensional space in Figure 3 (b). From the time-series data, we can make n-dimensional vector with delay-embedding. The vector can be expressed as below,

$$X(t) = [x(t), x(t+T), x(t+2T), \cdots, x(t+nT)]^T \tag{2}$$

where t is sample time and T is sampling period and n is dimension of the phase space.

As the time-series data is generated more, the vectors forms the trajectory. For calculation of LLE, it is required to find the nearest vector on the trajectory from the latest input vector. The distance between the input vector and the nearest vector on the trajectory can be described as below

$$d_{min}(t_0) = \left\| X_t(t_0) - X_k(t_0) \right\| \tag{3}$$

then, comparison of the next vectors evaluates the distance between them. Expression (4) shows the relation of the input vector and its next vector.

$$d_j(t_1) \approx d_{min}(t_0) \cdot e^{\lambda_0 (t_1 - t_0)} \tag{4}$$

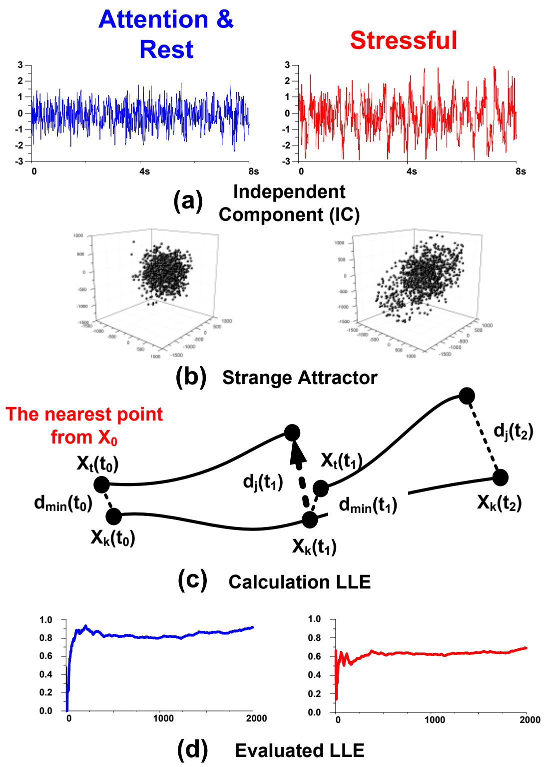

Figure 3 Calculation of NCA

$$\lambda_0 = \frac{1}{t_1 - t_0}\ln\frac{d_j(t_1)}{d_{min}(t_0)} \tag{5}$$

the λ is defined lyapunov exponent. From the calculation of every input vector, LLE is expressed as below.

$$\lambda_l = \lim_{n \to \infty}\frac{1}{n}\sum_{i=0}^{n}\lambda_i \tag{6}$$

for a long time, by averaging the temporal lyapunov exponent, LLE can indicate how much system behaves in chaotic way. The averaged values are shown like Figure 3 (d). If LLE is positive value, it means that the system is chaotic and unpredictable. In addition, the larger LLE is, the chaotic the system is.

C. Experimental Protocol

The 10 subjects participated in this experiment. They are healthy and never have mental disease such as anxiety and mood disease. The mean and standard deviation of the participants' ages is 25.1 and 1.88, respectively. The signals are acquired with proposed system instead of the hospital instruments. The analysis is performed in the PC.

Now the experimental protocol will be described in Figure 4. Three different stressful experiments are scheduled. The first one is emotional stress. On the screen, gross pictures are shown and the screen is changed every 20 seconds. For 3 minutes, this condition is maintained. The second one is temporal memory test. As the subjects play the different picture games, they are under the pressure to find the difference between two pictures. The last stressful environment is Sudoku puzzle. It is expected to tell the change

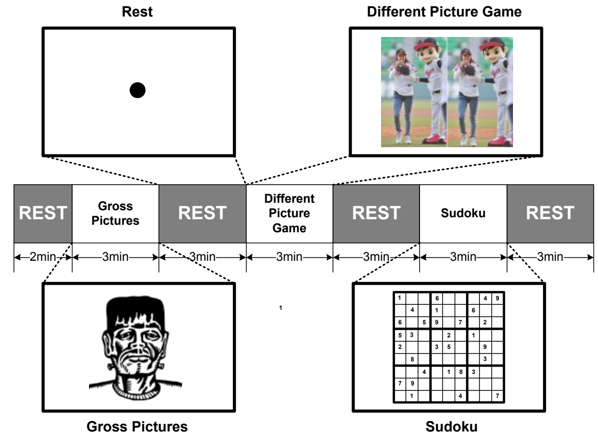

Figure 4 Experimental protocol

of physiological signals when the subjects perform the mathematical calculation. In the beginning and the period between each stressful test, the attention and resting periods are scheduled. During this period, the screen shows the point for the subject focus to it. The overall test takes 20 minutes.

III. Measurement Results

Figure 5 shows the performance of ICA to extract HRV signal from the EEG signals. The amplitude of ECG component is attenuated to 1/15 of the ECG which is acquired with ordinary ECG measurement setup. If peak detection of ECG component is performed without ICA, the error rate of peak detection is as much as 5.94%. On the other hand, with ICA, the difference is reduced to 1.84% compared with HRV with hospital instruments.

Figure 6 shows the LLE value of IC from EEG signals. The number of attractor points is 1024 and the dimension of the attractor is 4. The embedded delay is set to 4 samples.

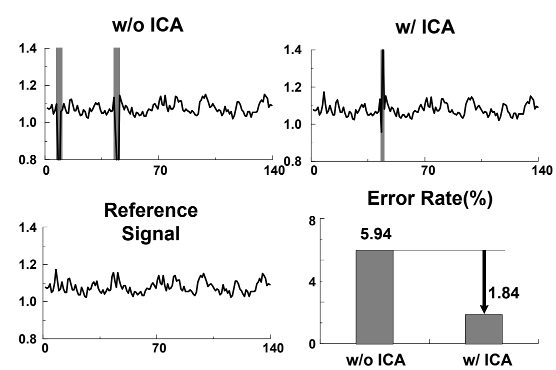

Figure 5 HRV extraction with ICA

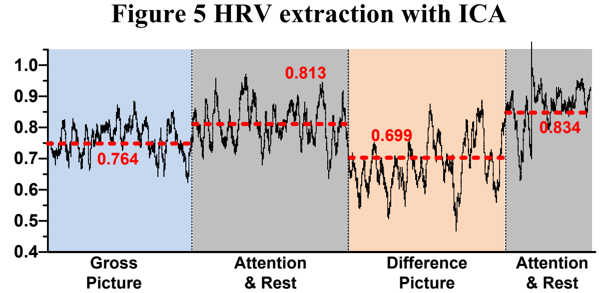

Figure 6 LLE variation vs. task

Table 1 Summary of feature analysis

	Attention & Rest	Stressful
EEG (LLE)		
Mean	0.810	0.734
Std. Deviation	0.048	0.077
HRV(RRV)		
Mean	951ms	947ms
Std. Deviation	63.7ms	73ms
Correlation Dimension (D2)	2.40	3.19

Depending on the task, the mean value of LLE is varied. For the stressful period the LLE value decreases to 0.734 and the standard deviation of HRV increases to 73ms. The overall scores are summarized in Table 1. The standard deviation of heart rate, which is main stress index, increases in the stressful environment.

IV. SYSTEM IMPLEMENTATION

In order to calculate the feature from the measured signals efficiently, [5] is used as the processor for ICA and NCA. Figure 7 shows the overall architecture of the processor. It has 4 channel analog front-end for EEG acquisition, two accelerators – ICA and NCA, a wireless communication block and a RISC. The sampling rate of EEG acquisition is scalable from 256 Hz to 1 kHz. The 10b analog-to-digital converter (ADC) transmits digitized EEG signals into the processor. With ICA and NCA accelerator, the cycle time is reduced by 1/1500 compared to the ordinary RISC processor.

The proposed headband system consists of the planar fashionable circuit board (P-FCB) platform and several fabric electrodes (ϕ = 1cm) as shown in Figure 8. The electrodes are connected by conductive threads. The reference and ground electrodes are located in the both sides to contact to the user's ear (A1, A2). Other signal electrodes are positioned in frontal, occipital head and above the nape (Fp1, O1, T5, T6). The headband system has external Bluetooth module to communicate with external device such as PC and mobile phones. It is as light as 50g and flexible so that the user can use it easily and comfortably. With 1.2V and 100mAh battery, it can last for over 4 days.

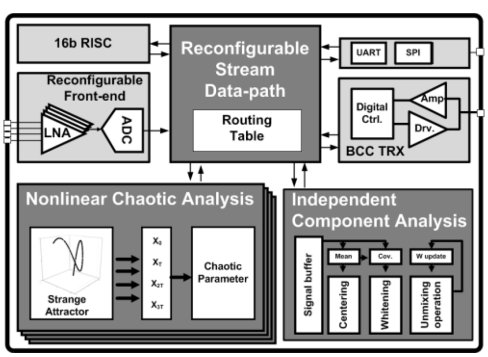

Figure 7 Top architecture of the processor

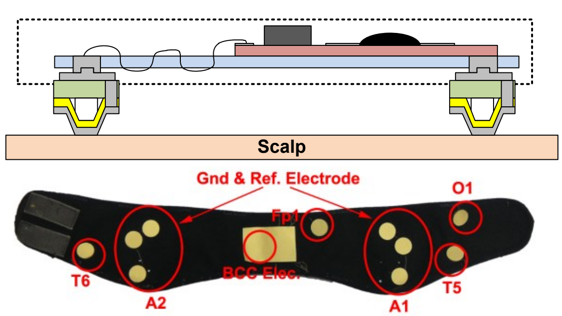

Figure 8 Overview of headband system

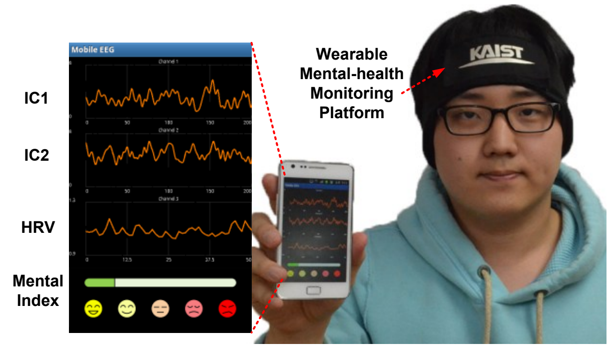

Figure 9 Demonstration of headband system

The mental health monitoring system is demonstrated with Android application on the smart phone as shown in Figure 9. The application shows EEG and HRV signals and the extracted stress index. The data can be stored and transmitted to other experts to be diagnosed.

V. CONCLUSION

The low-power and light-weighted mental health monitoring system is proposed in the shape of the wearable headband. The total weight of the proposed system is about 50g. The electrodes are attached to the headband so that user can wear the headband and measure the mental state easily. The platform can classify the mental stress with analysis of EEG and HRV. As the result of the analysis for LLE with 90% of confidence, its change correlates to stress index and it reacts to the stress. HRV is qualified with 1.84% of error compared with hospital system. The specific hardware for ICA and NCA helps to demonstrate the wearable mental health monitoring system. The graphical interface using PC and smart phone is introduced and represent the user's mental state in real time.

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