Stress monitoring using multimodal bio-sensing headset

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Abstract

Exposure to continuous stress can have a negative impact on a person's mental and physical well-being. Stress monitoring and management, with the aim to analyze or mitigate the effects of stress, are an active area of research. A promising approach for detecting stress is by measuring bio-signals such as an electroencephalogram (EEG) or an electrocardiogram (ECG). In this study, we introduce a wearable in- and over-ear device that measures EEG and ECG signals simultaneously. The device is composed of dry and soft sensing electrodes which are conformally integrated on the surface of earbuds. We carried out a pilot study exposing test subjects to three standard stressors (stroop, memory search, and mental arithmetic) while measuring their EEG and ECG signals. Preliminary results indicate the feasibility of classifying various stress conditions using a convolutional neural network.

Author Keywords

Wearable; Biometric Sensing; Stress detection; machine learning; CNN.

CCS Concepts

•**Human-centered computing** → *Ubiquitous and mobile computing;* •**Hardware** → *Sensor devices and platforms;*

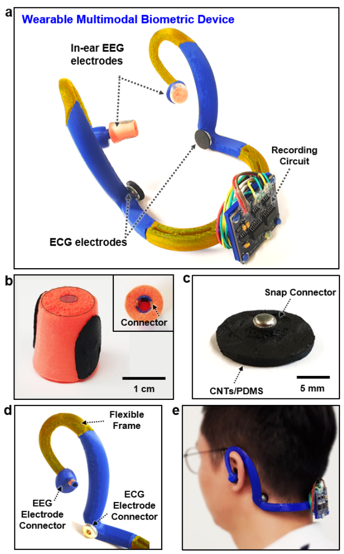

Figure 1: Proposed multimodal biometric sensing wearable. (a) In-and over-ear biometric sensing device with EEG & ECG electrodes and signal recording system. (b) Detailed view of the in-ear EEG electrode (c) Detailed view of over-ear ECG electrode. (d) Magnified image of designed ease-access connectors structures. (e) User wears proposed prototype.

Introduction

Stress is defined as human body's unspecific reaction to a perceived mental, emotional or physical distress [11]. Chronic stress is one of the major factors involved in several medical diseases including depression, cardiovascular disease, stroke, and even cancers [3, 12, 17]. Evaluating and managing stress in everyday life is important because early detection of stress may help prevent severe health problems. Traditionally, stress has been measured and evaluated by questionnaires, and chemical and physiological methods [7, 10, 20]. Recently, physiological stress detection methods that combine various signals have become popular due to their ease of access and fast response, and as they enable continuous monitoring. The Electroencephalogram (EEG) and the Electrocardiogram (ECG) have shown to be among the most promising physiological bio-signals for the detection of stress levels. [1, 3]. Previously, researchers showed that simultaneously recording EEG and ECG signals in combination with machine learning (ML) techniques has the potential to improve the accuracy of stress assessment [6]. More recent works have adopted a wearable form factor for recording biosignals [5]. However, measuring both EEG and ECG signals in a single wearable device remains challenging due to limited and localized on-body signal collecting spots [8]. Moreover, current wearable biometric signal measuring devices are often impractical due to their obtrusive designs [4, 14].

Here, we present a wearable in-and over-ear biometric sensing device that measures EEG and ECG signals simultaneously and evaluate its performance for stress detection. We propose a novel sensing electrode which is highly conductive, dry and flexible(as shown in Figure 1). It was designed with portability and comfortable long-term usage. It is worth noting that our design realized simultaneously recording of ECG and EEG signal with a highly integrated single-volume device for the first time. In this pilot study, biometric signals were recorded using from test participants subjected to three standard stress inducing experiments. A convolutional neural network (CNN) was trained to classify stress conditions from the biometric signals. The experimental results suggest that the proposed bio-sensing headset records signals directly applicable to stress detection and monitoring.

Related Work

Stress detection has been widely investigated in the area of physiological signal measurement. Heart rate variability (HRV), Electro dermal activity (EDA), electromyogram (EMG), and body movement are the most widely used physiological signals for stress detection [21]. By combining various biosignals, e.g., HRV and EDA, two-class stress classification with an accuracy of around 90 percent was shown previously [2, 5]. Using a 14-channel head-worn EEG system, it was reported 89 percent accuracy for classifying four stress levels [19]. However, a standard EEG recording device is not suitable for daily use due its weight, design, and lack of portability [4, 15]. We introduce an EEG and ECG sensing device in a headset form factor.

In- and Over-Ear Biometric Sensing Device

we propose a wearable in- and over-ear biometric headset designed as a sports earphone that offers reliable signal recording (Figure 1(a)). The mechanical frame was designed and fabricated using a 3-D printer (Ultimaker Cura) with a combination of rigid (blue frame composed of ABS) and flexible materials (yellow frame composed of thermoplastic polyurethane). A pair of in-ear EEG electrodes and over-ear ECG electrodes were integrated on each side of the frame. One common ground electrode was placed in the left ear for both EEG and ECG signal measurement. An integrated recording circuit was embedded on the back of

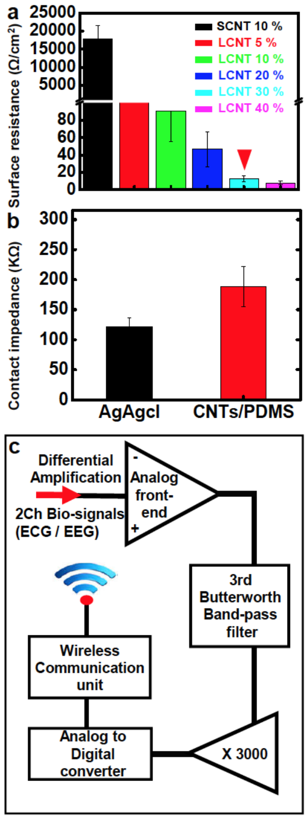

Figure 2: Electrode and system characteristics. (a) Electrical characteristics of dry-type CNTs/PDMS electrodes fabricated using different CNT types and weight percent. (b) Skin-electrode contact impedance comparison between CNTs/PDMS electrode and commercial Ag/AgCl electrode. (c) System overview.

the device and connected to the electrodes with a harness. The fabricated conductive and flexible dry electrodes were integrated as both EEG (Figure 1(b)) and ECG electrodes (Figure 1(c)). The electrodes and measurement circuit were connectedby snap button connectors allowing ease of electrode replacement when necessary (cf. Figure 1(d-e)).

Sensor Fabrication and System

Due to the small signal amplitude of EEG and ECG measured at the ear (on the order of few µV), the sensing electrodes should be highly conductive and the measurement system should offer high signal amplification. The advantages of composite dry electrodes for wearable systems include low cost, ease of manufacturing, and good skin conformability without dehydration. Conductive carbon nanotubes (CNTs) and polydimethylsiloxane (PDMS) were mechanically mixed together to form CNTs/PDMS composite as a sensing material. Electrode sheet resistance changes as a function of the average length of CNTs (20 µm for short CNT, *SCNT*; 100 µm for long CNT, *LCNT*). Mass loading of CNTs in PDMS matrix (10 wt % of LCNT) directly influences electrode sheet resistance which was optimized by adding high wt % and long CNTs to PDMS (Figure 2(a)). The skin-electrode contact impedance at 30 wt% LCNT of the optimized condition was equivalent to that of commercial (Ag/AgCl) wet electrodes (Figure 2(b)).

To enable reliable recording of small-amplitude signals in a frequency range of 0.5–30 Hz (characteristic signals of interest), the EEG and ECG signals pass through an analog front-end (INA 118, Texas Instruments Inc.), third-order Butterworth band-pass filter (fc = 0.5–30 Hz), 3000-times signal amplifier (OP497, Analog Devices Inc.) and a 1 kHz A/D converter (AD974, Analog Devices Inc.) (cf. Figure 2(c)). The signals were finally transmitted to a microprocessor (32

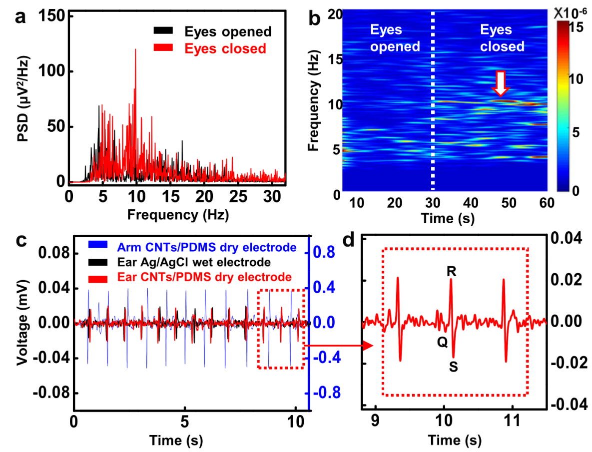

Figure 3: (a) Power spectral density and (b) Spectrogram of EEG signal, exhibiting alpha wave near 10 Hz; (c) ECG signal from dry CNTs/PDMS electrode at arm (blue) and ear (red), and reference wet Ag/AgCl electrode at ear (black); (d) ECG QRS peaks.

bit ARM Cortex-M4) and transferred by a Bluetooth module (Bluetooth Mate Silver, SparkFun Electronics).

EEG and ECG Signal Measurement

In accordance with the standard EEG and ECG paradigm, alpha rhythm detection and QRS peak detection were conducted for feasibility validation. In the EEG measurement, the right in-ear source electrode, left in-ear reference electrode, and left in-ear ground electrode were used. Subjects were instructed to close their eyes for 30 seconds (s) during the 60 s recording. The alpha peak was measured near 10 Hz while eyes were closed, as shown in the power spectral density in Figure 3(a). The EEG spectrogram showed highly detailed information including the time, frequency

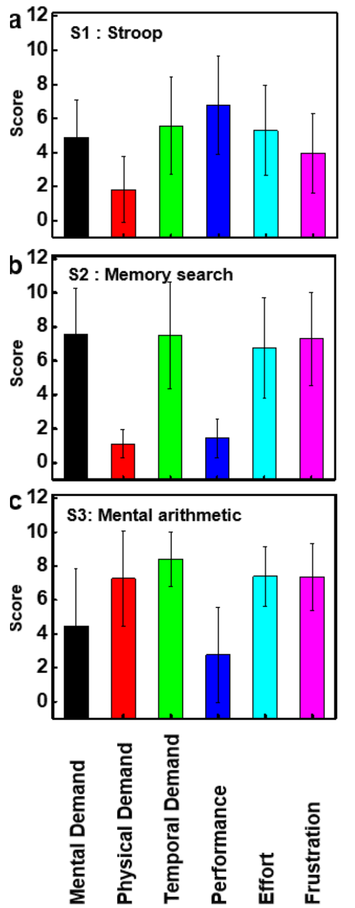

Figure 4: Questionnaire results for (a) Stroop, (b) Memory search, and (c) Mental arithmetic task.

and power of the EEG signal (Figure 3(b)). For the ECG detection, signal collection was based on using electrodes which are under the right ear as source electrode, under the left ear as reference electrode, and left in-ear as ground electrode, respectively. In addition, to evaluate signal quality influenced by electrode position , additional electrodes were attached on arms according to the standard limb lead 1 position [18]. The conventional Ag/AgCl wet electrodes were attached at the same locations for comparison. The overall amplitude of the over-ear ECG (red line) was much lower than that of standard ECG (blue line) due to their closer distance to the heart.However, the signal quality of the dry electrodes was found to be similar to the commercial wet electrodes (black line) and clear QRS peaks were detected in over-ear ECG (Figure 3(c)).These results confirm that the developed biometric device enables simultaneous measurement of EEG and ECG signals with high signal quality.

Experimental Evaluation

We recruited ten healthy subjects (mean age 29$\pm$5 years) for a pilot study to conduct bio-signal measurements under stress. The subjects were asked to perform three certified tasks to induce stress: Stroop, memory search, and mental arithmetic [3]. The experiments were divided into separate sessions, as illustrated in Figure 5. Each experiment consisted of 3 minutes of stabilization, 90 seconds of relaxation, and 3 minutes of a stress-inducing task. Before starting the main user test, a stabilization period is established before relaxation period during test preparation. Simultaneous in-ear EEG and over-ear ECG were acquired throughout the experiments. After each session, subjects were asked to complete a NASA-TLX questionnaire to obtain an additional qualitative stress index [9]. This method also ensures effectiveness stress stimulation. According to the questionnaire, the performance and frustration questions were used mainly to measure the perceived stress

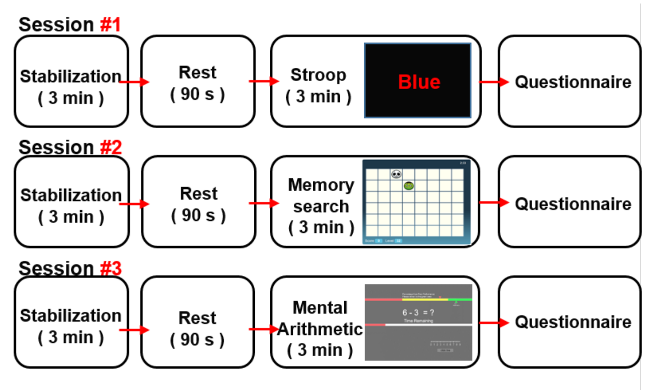

Figure 5: Experiment protocol.

level of the subjects; a low score for the performance question and a high score for the frustration question indicates a subject's elevated level of mental stress. The stroop task (Figure 4(a)) induced weaker stress levels than memory search (Figure 4(b)) and mental arithmetic (Figure 4(c)), as shown by higher performance and lower frustration scores.

Stress Detection Results

Neural networks have shown promising results for analysing raw time-domain EEG signals [13]. We trained a similar neural network to classify the experimental data of the pilot study as "stressed" or "relaxed". The raw time-domain EEG and ECG signals were split into frames of 30 s with 25 s overlap. All signals were resampled at 128 Hz and preprocessed using a 60 Hz notch filter and a 1–40 Hz bandpass filter. The classifier was trained separately for each subject with 3-fold cross validation, using the data from two experimental sessions for training and evaluating the performance on the third hold-out session (cf. Figure 5). To avoid bias, the signals from each session were trimmed to

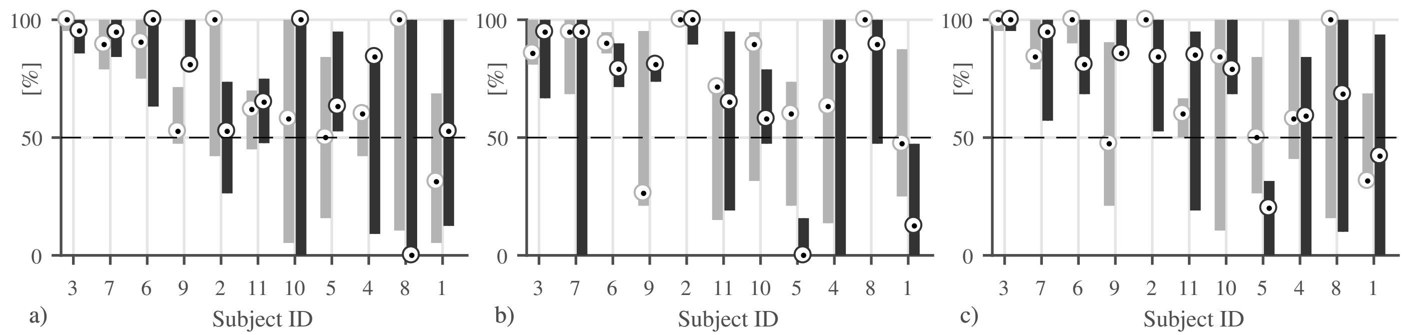

Figure 6: Box plots of per-frame classification accuracy for relaxed (light gray) and stressed condition (dark gray), for (a) EEG, (b) ECG, and (c) EEG and ECG combined. Subjects are sorted from highest to lowest average combined classification accuracy.

ensure an equal number of "relaxed" and "stressed" frames, for an average of about 19 frames per session and class for each subject. The neural network consists of four dilated convolutional layers with rectified linear unit (ReLU) activation, batch normalization, and max pooling. These first four layers form a convolutional neural network (CNN) used to extract features from the raw time-domain signals. Implementation details of the CNN are given in Table 1. The final convolutional layer is followed by a 50% dropout layer, a fully connected layer with eight hidden units, and a final linear layer with two outputs corresponding to the two classes "relaxed" and "stressed". The neural network was implemented in PyTorch 1.1 using default functions and parameters and trained over 100 epochs using stochastic gradient descent and negative log-likelihood loss, with a batch size of 64 and a learning rate of 0.001.

Figure 6 illustrates the per-frame classification results of the neural network. Performance varies greatly by subject. This may be attributed to a variety of factors, including measurement noise and individual differences in terms of the stress levels experienced and the fit of the proposed biometric measurement device given each subject's individual signal topology [16]. Figure 6c) shows per-frame classification results obtained by assigning the output of the EEG and ECG classifiers with the highest probability (i.e., the maximum negative log-likelihood) to each frame.

	layer 1	layer 2	layer 3	layer 4
number of filters	6	8	12	12
kernel	1×8	1×8	1×4	1×4
stride	1×2	1×2	1×2	1×2
dilation	1×1	1×2	1×2	1×2
pool kernel	1×3	1×3	1×3	1×3
pool stride	1×2	1×2	1×2	1×2

Table 1: Convolutional neural network (CNN) architecture.

Table 2 summarizes the classification results for EEG, ECG, and the combined classifier. As can be seen, combining the EEG and ECG classification results leads to slightly improved average per-frame classification performance. To

	per-frame		per-session	
	“relaxed”	“stressed”	“relaxed”	“stressed”
EEG	67.1	69.0	72.7	78.8
ECG	73.1	63.2	75.8	66.7
combined	72.3	68.4	75.8	75.8

Table 2: Percentage of correct classifications, averaged over all test subjects and experiment sessions.

arrive at a single classification per subject and experiment session, a voting strategy is employed whereby for each session the most frequent classification output is chosen as the per-session result. The average per-session classification accuracy exceeds 70% for all conditions except for the ECG classifier and the “stressed” condition.

Conclusions and Future Work

We introduce a wearable in and over-ear biometric sensing device to monitor stress conditions via multimodal physiological signals. The proposed device is able to detect stress by simultaneously recording EEG and ECG signals with robust signal quality. The nano-materials flexible electrodes offers robust bio-signal recording while providing user comfort. A pilot study suggests that a neural network is capable of classifying relaxed and stressed mental states of a user by analysing two minutes of EEG and ECG signals obtained with the proposed device, with an average accuracy of about 75%. We believe that the design reported in this study has significant potential in active and social bio-signal measurement applications. The stress detection in this paper was conducted in laboratory conditions. However, we envision that the proposed wearable biometric sensing device can be used in various daily activities. Future work includes field studies in a larger variety of stress-inducing conditions. Collecting data from a larger subject pool would allow improving classification performance as well as training and evaluating a between-subject classifier that does not require per-subject training.

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