

Feasibility of a low-cost platform for physiological recording in affective computing applications

Hamed Monkaresi, Rafael A. Calvo

School of Electrical and Information Engineering, The University of Sydney, NSW 2006, Australia
hamed.monkaresi@sydney.edu.au, rafael.calvo@sydney.edu.au

ABSTRACT

Physiological signals provide valuable information about human physical and mental states. For decades, sophisticated equipment has been used to measure them in health and psychological applications. More recently a variety of low-cost portable electronic devices and smart-phone applications are being used to measure physiological signals. The accuracy of these devices has not been evaluated in medical or practical affective computing applications. In this article, we evaluate a low-cost, Do-It-Yourself, and open-source device that can measure multiple physiological signals. The accuracy of this platform in measuring ECG signals has been examined and compared with a commercial psychophysiology system. In addition, we evaluate the feasibility of using this platform in affective computing applications.

1. INTRODUCTION

New devices for monitoring physiological signals are becoming mainstream consumer products. Most of the new smartphones are able to track heart rate and the activity of the user. Another set of wearable products such as Fitbit, Samsung Gear and the Apple watch can also be worn all day and night, even in the shower. Users can monitor their day to day activities and physiological changes in a low-cost simple way. Physiological signals were one of the first modalities explored in Affective Computing (AC) studies [1] due to the view that the human body produces different physiological patterns in response to each specific affective state. It is yet to be shown that wearable devices are accurate enough to be used in conjunction with AC techniques [2] to automatically detect emotions, stress and cognitive load in everyday situations.

2. METHODS AND MATERIALS

In this study, we developed an open-source software platform called JSiento [3] to receive, process and store physiological signals. The e-Health platform v2.0 [4] one of the popular open-source and low-cost platforms for measuring physiological signals was used in this study. The source code provided by the manufacturer for measuring ECG signals does not acquire the signals properly. There were a couple of issues embedded in the source code which made unwanted delays in sending data. We revised the source code and added a timer to measure and send the data every 4 milliseconds. Using the revised method the physiological signals are collected at a sampling rate of 250Hz.

The BIOPAC MP150 system was used to acquire reference physiological signals at a sampling rate of 250 Hz. The BIOPAC measurements were used as the reference for our comparisons. The ECG features were extracted based on the important points on PQRST waveform and were used to classify participant's affective states. The main ECG features extracted are P-, Q-, R-, S-, and T-peaks, PQ, QS and ST segments, P-, Q-, and R-amplitudes and

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HRV. A variation of statistical features such as mean, median, minimum, maximum, range, etc. were extracted from the mentioned basic features.

3. EXPERIMENT

Twenty healthy participants volunteered to take part in this study (12 Females, 8 Males; mean age of 26.75 years). Two distinct sessions were recorded for each participant. In the baseline session, the ECG signals were recorded. The three electrodes from the e-Health platform were plugged on the participant's chest. The electrodes of the BIOPAC system were also placed next to the corresponding electrodes in almost the same area. A set of emotional images selected from International Affective Picture System (IAPS) database was shown to the participants in the AC session. Each image was shown for 10 seconds. Normative valence and arousal scores converted into binary scores. A vote classifier was used to combine the results achieved by four base classifiers with the average probability rule. Two sampling time windows were used for segmentation: image-level features were extracted from fixed 10-seconds time windows correspond to each image. Block-level features were extracted from larger time windows correspond to a group of images which had the same binary ratings.

4. RESULTS

Evaluating the Pearson r values for the signals recorded in the baseline sessions showed that 10 out of 13 ECG features had almost the perfect match with the reference values ($r > .90$, $p < .01$). The calculated HRV had also significant strong correlation with the reference values for the signals recorded in the AC session ($r_{\text{image-level}} = .94$, $r_{\text{block-level}} = 1$, $p < .001$). Compared to the image-level features, stronger agreements were observed for block-level features. The average Cohen's Kappa scores of .363 and .345 were obtained for valence detection using JSiento and the BIOPAC features respectively. The average Kappa scores of .150 and .196 were achieved for arousal detection for using JSiento and the BIOPAC features respectively. These accuracies were also comparable with similar physiology based affect detection systems [5] which showed the feasibility of using a low-cost and portable physiological sensing system in a practical AC application.

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