Real-Time Data Evaluation with Wearable Devices: an Impact of Artifact Calibration Method on Emotion Recognition

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January 10, 2022

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Abstract- ***Smartwatch technology is transforming the environment of transmission and monitoring for stakeholders and research participants who want to provide real-time data for evaluation. A range of sensors are available in smartwatches for gathering physical activity and location data. The combination of all of these elements allows the collected data to be sent to a remote computer, allowing for real-time monitoring of physical and perhaps emotional development. Photoplethysmographic is an uncomplicated and inexpensive optical measurement method that is often used for heart rate monitoring purposes. PPG is a non-invasive technology that uses a light source and a photodetector at the surface of skin to measure the volumetric variations of blood circulation. Models with respect to HRV (Heart Rate Variability) analysis are being studied in a variety of domains, including human emotion recognition (HER). Smart watches as sensor-based devices play an important role as, photoplethysmographic (PPG) data are frequently evaluated for this assessment. However, the quality of these signals (in terms of additional disturbances) may not always be optimal, as they are vulnerable to a variety of parameters, such as motion artifacts, light sources, stress distribution, ethnic background, or circumstances. Here techniques for artifacts rectification play a significant role &, as a response, have an impact on the outcome. This research proposes a novel data distortions mitigation strategy for improving emotion detection classification efficiency using PPG signals during auditory stimulation and a Support Vector Machine (SVM) model. In comparison to data which was before undertaken using a conventional toolset i.e.,48.81, the presented scheme provides an improved categorization in trigger sensing i.e., 68.75 percent. For further improvement an alternative indicator, such as electroencephalographic activity, could be used in conjunction with PPG for additional improvement.***

Keywords – Smartwatch as Sensors, HRV, PPG, human emotion, support vector machine (SVM).

I. Introduction

Human emotions are feelings about an occurrence or a piece of work that are tied to mood, disposition, personality, and motivation. Facial expressions, voice, text, gestures, and bio-signals are all examples of biological and physical reactions that can be used to represent them.

Despite advances in human–computer interaction (HCI), identifying human emotional states remains hard, making it difficult for robots to create the impression that they actually understand humans [1][2]. Heart Rate Variability (HRV) analysis, which measures the physiological variation of the heart rhythm due to autonomic transmission, can be used to assess a variety of health issues, including high blood pressure, mental and physical anxiety, hypertension, hypoglycemia, childbearing, and human emotions[3][4]. Physiological parameters such as electroencephalography (EEG), electromyograms (EMGs), photoplethysmograms (PPGs), inhalation patterns (RSP), and electrocardiogram (ecg) are crucial criteria for emotion detection within sensory data because they are impulsive actions[5][6]. Previous research have used HRV analysis to promote understanding caused by emotional sounds, particularly in terms of diversity in the assessment of inter-beat-intervals (IBIs) [7]. Because PPG is prone to dynamic disturbances, using an appropriate artefacts reduction approach is critical. For this goal, three basic strategies may be identified: removal, interpolation (using various approaches such as nearest neighbours, cube smoothing, or piece - wise cubic Hermite), and intelligence efforts. The rectification of incorrect IBI readings can be done by taking into account the surroundings IBIs over a short period of time [8],[9],[10]. The PPG sensors can be placed in the fingers, ears, forehead, and wrist to evaluate human parameters. It's difficult to effectively estimate human parameters from the wrist since the wrist is particularly vulnerable to body motions that distort the PPG signal, that determines the performance[11][12]. The overall goal of this study is to increase the efficiency of sentiment identification systems that use features retrieved from HRV analysis to perform categorization. As a response, this paper provides a new method for correcting anomalies in IBI time series based on replacing missing sounds with the average value of the beats preceding and following the explained variable. During studies generating emotions using audio samples from the IADS-2 databases, IBI signals from a PPG sensor (Empatica E4) were taken into account. The impact of the artefact calibration method on the data was then assessed by comparing it to the Kubios toolbox's artefact repair strategy [13][14]. The Support Vector Machine (SVM) algorithm had been used to detect the presence or absence of stimuli, using as input parameters those found with statistically significant using a baseline t-test. A forearm, multimodal smartwatch (Empatica E4) has been utilized for investigation to capture a range of physiological parameters from which features are extracted for feeding, with the goal of detecting an audio stimulus. Fig. 1 illustrates the planned execution process.

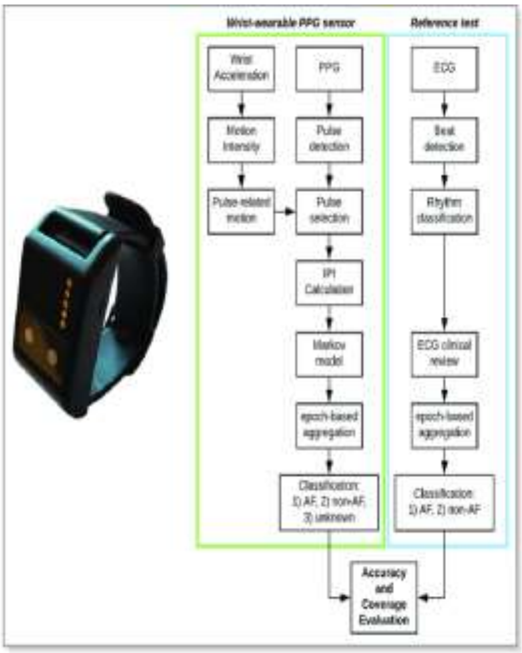

Figure-1 Illustrates execution process of PPG sensing flow

II. Background & related work

A. Protocol for testing

Before the data collection began, each participant was given a full explanation of the experiment and accepted an explicit permission form. The research setup is depicted schematically in Fig. 2. For the purpose of analyzing the emotion reaction, test respondents were requested to concentrate as much as possible on the generated stimuli. The participants were positioned in a supine position in a quiet room, with their eyes shut, to allow them to rest as much as feasible and prevent interfering with the testing process. In pursuance of this the studies were conducted on a small group of healthy volunteers, 2 males and 5 females, ranging (36 to18) years (average absolute variation), and with a BMI ranging (22.7 to 2.1) kg/m^2. As shown, PPG data includes the initial calibrated time of around 15 seconds, after which the readings in this time interval are eliminated from further processing. Three stimuli are shown below, each with a different intensity.

- ✓ Pleasant sample of approx. 810
- ✓ Natural stimulus of approx. 715
- ✓ Unpleasant sample of approx. 300

Figure-2 Empatica E4 Measurement setup

Each acquisition lasted approximately max10 minutes, the first 5 minutes were spent in resting state to obtain the foundation of IBI values, and the second included 1 minute of audio stimulus (repeated 10 times, since each sound in the IADS dataset lasts 6 seconds) and 4 minutes of resting, as shown in Fig. 3. Patients were told to push the wristband's event-marker button at the start and conclusion of each sonic stimulus in order to facilitate real-time comments of the sound checks[15].

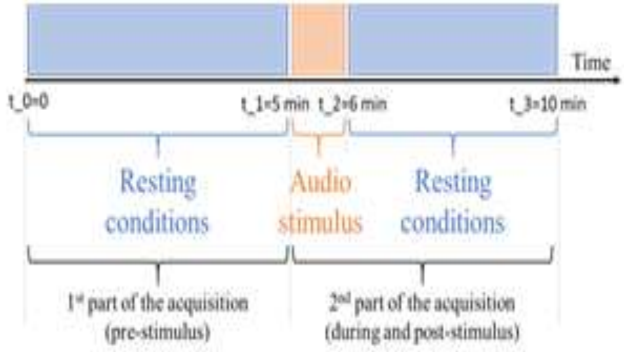

Figure 3 Two-part HRV Analysis

B. Device for taking measurements

Photoplethysmography uses light transmission or reflection to determine the proportional change of the heart. Systolic pressure in the left ventricle, the main pumping chamber, rises as the heart contracts [16]. The signals created by the PPG sensor were taken into account (even if all four impulses were obtained); in specifically, the PPG sensor generates the Blood Volume Pulse (BVP) signal, which can be used to determine the Heart Rate (HR) and IBI signals. The PPG sensor, which is located on the bottom of the device and in close proximity to the subject's skin, is made up of four photodetectors (2 green, 2 red) that allow the computer to quantify blood volume changes related to the cardiac cycle, as well as two photodiodes (14 mm2 of sensitive area)[3],[16].

The sensor's digital signal is a change in light intensity (resolution: 0.9 nW/Digit). The green light includes the most important information about the pulse wave, while the red light is used to regulate motion artifacts appropriately. In reality, the Empatica E4 includes an artifact prevention algorithm (which uses sensor data to detect motion abnormalities) that allows for the registration of IBIs derived from a noise-free PPG signal alone. Data that has been deleted cannot be retrieved in any way [17][18].

In addition, the geological aspects of the device used to acquire the sound undoubtedly impact data accuracy ; for example, it was reported in an earlier study that Empatica E4 correctly recognizes heart beating for 68 percent of cases during resting and only for 9% during domestic duties, demonstrating the greater vulnerability to motion artifacts [19].

C. Preparation of data

In the programming environment, the data was pre-processed. IBI signals, in particularly, were investigated; they consist of two columns of data, the first of which reports the time. The chosen data's permanents (in seconds, s), the latter showing the measured time difference values in seconds (s) since the last beat which is RR interval. When data is distorted by motion noise, samples are not recorded in the.csv file, implying that the created tachogram (i.e., a sequence of successive RR intervals) is incomplete. To perform an accurate HRV analysis without the effect of artificial frequency components introduced by absent beats, a good technique for artifact concealing is required[16].

D. Methods of feature extraction

Two different corrective strategies were evaluated in the current study to eliminate spiking that would create erroneous frequency components: the interpolation method offered within the Kubios tool, and a novel way proposed by the authors themselves. The latter ("Kubios Method) uses a linear/cubic spline interpolation to rectify the recognized aberrant pulses, taking into account a time-varying threshold determined from the distributions of consecutive IBIs [20]. Depending on the parameters made by the operators, this threshold can be set to the really low, low, moderate, strong, very powerful, or customizable. In this investigation, a 0.25-second middle threshold was chosen. On the other hand, the method presented in this study (hence referred to as “Proposed Method”) comprises of the phases seen in Fig. 4.

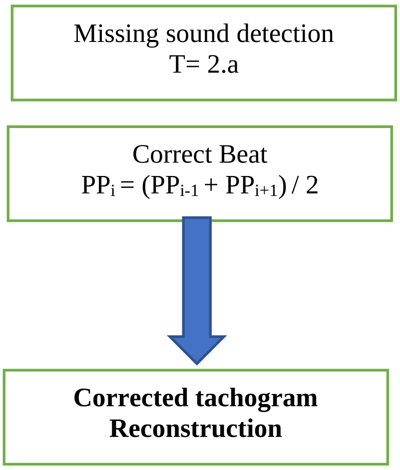

Figure 4 Correction tachogram flow (Here a= deviation between consecutive sampling time intervals & T is threshold)

III. Assessment of events and the impact of artifact treatment approaches on emotion classification

The student’s t-test was used as a preliminary assessment of the variations in HRV equations to describe with and without a stimulus (5 percent significance level). The 5-minute signals prior referring to the stimuli (t 0, t 1) and the 5-minute signals after and during listening to the stimuli (t 1, t 3) were used to create two sample members. The HRV parameters calculated by Kubios were subjected to statistical analysis. Here the factors that were more susceptible to stimuli were found using the t-test results. The selected parameters were then employed as response variable for a machine learning analysis, which included all those that reported statistical difference here between existence and absence of stimuli. The SVM classifier was chosen in particular because it is said to offer the greatest performance for HRV analysis. SVM is a racially prejudiced strategy that trains the enablement to class labels and creates the best decision surface that divides the dataset into two sets within the range of characteristics [21]. The efficiency, F-measure, sensitivities, and clarity of the categorization all were examined[13],[7].

(A) Accuracy = (1-errorrate) * 100 (i)

(B) Sensitivity = TP/(TP+ FN) (ii)

(C) Precision = TP/(TP+FP) (iii)

(Here TP denotes true positive FP False positive and FN false negative).

IV. Methodologies of artifact removal (Result)

The twin artifact correction methods, Kubios Method and Proposed Approach, are not equal, according to the findings. Figure 5 shows an example of a comparison between the two tachograms acquired. Visual observation of the tachograms produced by the two approaches does not reveal significant variations between the two graphs, but study of the variances between HRV parameters acquired from the data preprocessed by the two methods yields more useful results. It's important to note that the HRV parameters acquired for data pre-processed with the Kubios Method occasionally returned NaN (Not a Number) values. The data handled with the Proposed Method, on the other hand, did not have this problem.

With reference to figure 6 significant discrepancies between the two approaches revealed by the study of deviations lead us to conclude that they are not identical; this was validated by a Student's t-test done on all the parameters computed using the two methods (significance level: 5 percent). Further tests were undertaken based on this assumption to determine which of the two evaluated methodologies gives the best signal reconstructions and, as a result, the best recovered characteristics group in order to obtain the best SVM classification efficiency.

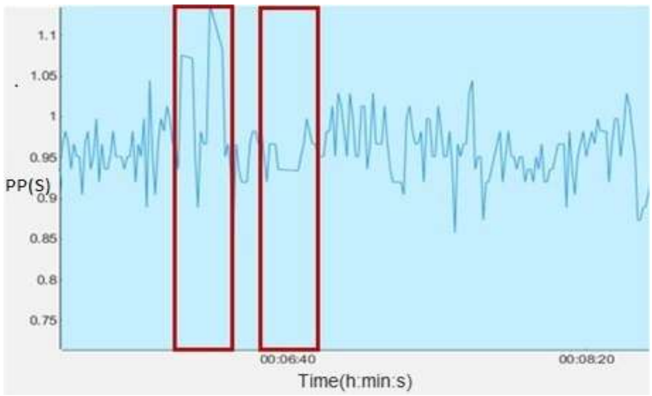

Figure 5 (a)

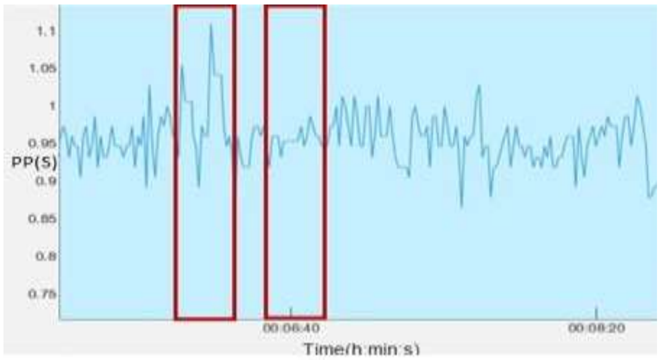

Figure 5 (a) and (b) show proposed methods tachograms comparison

V. Human Emotion recognition (Students t-test) & SVM Classifier

For the two artifact elimination procedures, the preliminary Student's t-test yields different findings. For data pre-processed using the Recommended Method, 17 factors with statistically significant variations between availability and absences of stimuli were detected, but only 3 for data corrected with the Kubios Method.[13]. Because the two methodologies were shown to be incompatible (both through investigation of variations and a t-test between HRV-related characteristics), it was hypothesized that the findings for emotion recognition would be different as well.

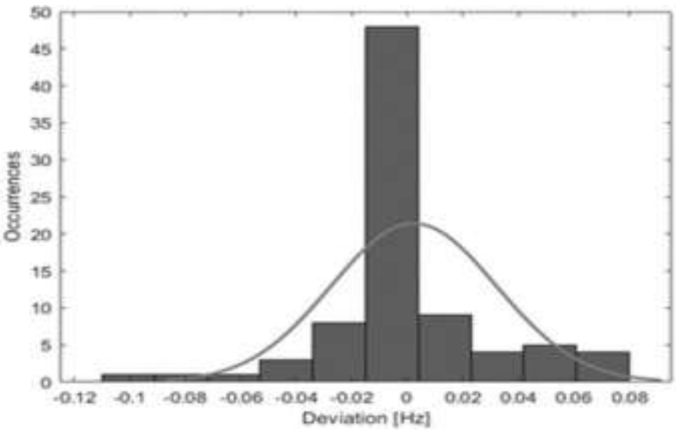

Figure-6 Distribution of LF_Peak Parameter[16]

The factors shown to have substantial differences in between existence and absence of a stimuli in both the Proposed Method and the Kubios Method data were then used to detect the existence of a stimulus using the SVM classifier. The authors chose the following input variables (for a total of 18 features) based on the analysis noted in previous paragraph and exploring statistically different settings with a higher significance level (5%).

The classification performance between the availability and absence of a stimulus for information pre-processed with the Process Of conversion was 68.75 percent, compared to 48.81 percent for data pre-processed with the Kubios Method. It's worth noting that, while using the Proposed Method to pre-process the data, all of indications with stimuli were correctly identified, whereas most of the indicators without stimuli weren't really. On the other hand, there were incorrectly classified signals for both the availability and absence of stimuli in the data pre-processed with the Kubios Method.

VI. Conclusion and discussion

Three various auditory stimuli were used to generate emotions in a group of few volunteers, and their performance of emotion categorization accuracy was tested. A preliminary Student's t-test identified the HRV parameters most affected by the emotional responses elicited by the stimuli; these parameters are defined inside the time - frequency domain, to ascertain the level of variability in the IBIs metrics; in the frequency response, to evaluate the distribution of absolute and relative power into four bandwidths; and the non-linear features, which allow to quantify the unpredictability of the IBIs time series.

A total of 18 features were discovered with a significance level of less than 5% among all the measures computed. Following that, the selected features were used as inputs for an SVM classifier to detect and categorize the existence of the auditory stimulus in the IBIs time series based on the emotional response. The results reveal that the suggested Method (accuracy: 68.75 percent) for artifact correction outperforms the Kubios tool (accuracy: 48.81 percent) calculated as a percentage of accuracy obtained by the SVM classifier. This stresses the significance of the artifact calibration method and its significant influence on the outcomes: The artifact reduction method used to pre-process the obtained data has a substantial impact on the capacity to distinguish the existence of a stimulus (considering solely its arousal).

The Proposed Process has the drawback of requiring an initial visual evaluation of the signal to detect missing beats; however, this could be automated in the future using an appropriate computational method. As a result, when attempting to recognize emotions, especially when both arousal and ionic are taken into account, it is critical to make appropriate choices from the evaluation bench to the classification, transferring through the sensor used and the signal processing technologies used to clarify data and obtain final results.

Multimodal observations can increase classification performance by providing a larger fingerprint that can be retrieved at various levels, making the emotion recognition task easier than if only a single physiological signal was used. As a result, in future investigations, the authors would like to look at other signals besides PPG, such as EDA, and compare the effectiveness of different classifiers using multimodal factors rather than just HRV characteristics.

VII. References

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