Detection of Essential Hypertension with Physiological Signals from Wearable Devices

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Abstract— **Early detection of essential hypertension can support the prevention of cardiovascular disease, a leading cause of death. The traditional method of identification of hypertension involves periodic blood pressure measurement using brachial cuff-based measurement devices. While these devices are non-invasive, they require manual setup for each measurement and they are not suitable for continuous monitoring. Research has shown that physiological signals such as Heart Rate Variability, which is a measure of the cardiac autonomic activity, is correlated with blood pressure. Wearable devices capable of measuring physiological signals such as Heart Rate, Galvanic Skin Response, Skin Temperature have recently become ubiquitous. However, these signals are not accurate and are prone to noise due to different artifacts. In this paper a) we present a data collection protocol for continuous non-invasive monitoring of physiological signals from wearable devices; b) we implement signal processing techniques for signal estimation; c) we explore how the continuous monitoring of these physiological signals can be used to identify hypertensive patients; d) We conduct a pilot study with a group of normotensive and hypertensive patients to test our techniques. We show that physiological signals extracted from wearable devices can distinguish between these two groups with high accuracy.**

I. Introduction

Hypertension is one of the most prevalent diseases of the modern world. According to a recent report [1] by the World Health Organization (WHO), hypertension affects more than 40% adults over the age of 25. In 2008 over 1 billion people worldwide were found to be suffering with hypertension. If left untreated it can lead to serious cardiovascular and cerebrovascular complications, and even death due to renal failure, heart attack or stroke.

The most common method of diagnosis of hypertension is the detection of the presence of high-blood pressure using brachial cuff-based measurement devices. These devices, however, require careful setup for each measurement, and they are not generally suitable for use outside clinical settings. While doctors have advocated the use of ambulatory blood pressure measuring devices for continuous monitoring, they are more commonly accepted among patients who are already hypertensive or have been diagnosed with high risk of hypertension.

Several studies have demonstrated that continuous increased activity of the sympathetic nervous system is indicative of health problems. Our sympathetic nervous system controls our "fight or flight" response [2]. Sympathetic over-activation leads to elevated heart rate, which increases cardiac output. Since blood pressure is a product of cardiac output, elevation of heart rate also leads to elevation of blood pressure. Measurement of Heart Rate Variability (HRV) has thus been shown to be an effective measure for the detection and prediction of hypertension [3]. Other Physiological signals such as Skin Temperature and Galvanic Skin Response (GSR), which are also indicative of the sympathetic activation, can also be of interest for the detection and monitoring of hypertension.

In the recent years, wearable devices with multiple connected sensors have made healthcare ubiquitous and patient-centric. Unlike ambulatory monitoring systems, wearable devices are mostly comfortable and aesthetic, and are being rapidly adopted by the general population. Devices like the *Basis Armband* [4], *Microsoft Band* [5], *Empatica Embrace* [6] amongst others, are capable of measuring multiple motion and physiological signals such as Galvanic Skin Conductance (GSR), Skin Temperature, Blood Volume Pulse (BVP), and Heart Rate. Such devices have opened up a great unprecedented opportunity for continuous remote monitoring and predictive diagnosis for various medical conditions.

Researchers have already achieved a wide level of success in the detection and monitoring of people suffering from stress, epilepsy, bipolar disorder, and sleep apnoea [7], [8], [9] using wearable sensors.

One major drawback of using wearable sensors is the presence of artifacts which can contaminate the signal. Artifacts can be caused due to motion, pressure, vasoconstriction due to cold weather, or nervous fidgeting [10]. Hence there is a need to develop effective signal processing methodology for artifact removal before these signals can be effectively used for experiments on supervised hypertension detection.

In this paper we implement a robust signal processing pipeline, and explore how individual and combinations of various physiological signals can be used to detect hypertensive patients. The paper is structured as follows. In Section 2 we describe our data collection and experimental design protocol. In Section 3 we describe the signal processing, artifact removal techniques, and results of our hypertension detection task.

II. Experimental Design

An observational Pilot Study was conducted with 10 Hypertensive and 10 normotensive adults for 10 days each. Adults (male and female) between the age of 30 and 65 were selected for the study. Patients who were suffering from

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essential hypertension (EH, n=8) and receiving treatment at the ***Centro Ipertensione Ospedale Molinette*** in Turin, Italy were recruited. The healthy control (normotensive) subjects were chosen by a psychologist to rule out hidden hypertension, and any other underlying health problem that might affect the study. The institutional ethics committee of the Azienda Ospedaliera Città della Salute e della Scienza di Torino and the ethics committee of the Università degli Studi di Trento approved the present research study. All data was anonymized before analysis.

The data collection protocol was the same for both reference groups. Each participant was provided with an Empatica E3 wearable wristband and an iPhone with an installed agent application capable of recording and securely transmitting the data to the university server. During the first interview the participants were instructed on how to use the wristband and application, and were evaluated by a psychologist on perceived stress and emotion regulation. During this interview they also signed an informed consent for participation.

The Empatica E3 wristband is capable of continuously recording multiple physiological signals. The goal was to monitor the participants during their work day. The participants wore the wristband everyday from morning (before leaving for work) till evening (till they returned home). They periodically answered questions and took notes regarding their mental state and current activity using the agent application.

At the end of the study, there was a counselling session with the psychologists to assess the adaptation of the protocol among the subjects, and to ensure the effectiveness of the study.

III. Data Analysis and Experiments

The goal of the data analysis is to discover features and trends from physiological signals which can be used to detect hypertension in people. While in literature the relationship between hypertension and blood pressure is well established, the detection of essential hypertension from other physiological signal streams and their fusion has not been comparatively investigated. Our goal is to design a signal processing and feature extraction & combination pipeline which can be applied to this task.

A balanced subset of 8 hypertensive and 8 normotensive subjects was selected for the experiments with respect to the completeness of the signals collected. A total of 756 hours of data from the hypertensive patients and 780 hours from normotensive control subjects have been analysed.

A. Signal Processing Techniques

The Empatica E3 reports Galvanic Skin Response (GSR) and Skin Temperature (ST) at 4 Hz, Photoplethysmograph (PPG) data at 64 Hz, and tri-axial acceleration at 32 Hz. Prior to any analysis, the signal streams need to be preprocessed for artifact removal and normalization.

When a subject wears the E3 device, there is initial local perspiration because of the contact of the device with the skin. This causes an initial rapid increase in the GSR signal which requires few minutes to stabilize. The Empatica E3 photoplethysmograph sensor also calibrates itself before it can start reporting the PPG data. Hence for every session, we remove the first five minutes. Then for each individual signal we preprocess it to decrease the amount of noise. For the GSR and Skin Temperature (ST) we first use a low pass Butterworth filter. Then we detrend the GSR to remove the temporal low frequency drift. The Empatica E3 performs on board signal processing to remove motion artifacts from the PPG signal [11]. However, we observed that the reported PPG data still contained certain local motion artifacts, which conditioned the resulting signal entropy. In the physiological signal literature, different methods have been proposed to remove artifacts from PPG data for the derivation of Blood Volume Pulse (BVP) and Heart Rate signals. Adaptive filters schemes [12], such as Normalized Least Mean Square (NLMS) and Recursive Least Square (RLS) [13], and smoothing algorithms (e.g. Moving average filters) [14] support the accelerometer subtraction for noise removal.

Active Noise Cancelation: We process the PPG signal with the Active Noise Cancelation method as proposed in [15] to derive a BVP signal. This method consists of a Least-Mean-Squares (LMS) adaptive algorithm, used to minimize the error with respect to the desired filter impulse response coefficients. In this paper we use the same approach as in [15], and define a $32nd$ order FIR passband filter as our desired response defined by $[0.5 - 5]Hz$ bandwidth. Concordantly, we selected a LMS learning rate of $\mu = 0.0021$ based on the maximum glitch and BVP extra beats attenuation presented in [15].

$$w(n+1) = w(n) + \mu \frac{\partial[\sqrt{e^2(n)}]}{\partial n} \tag{1}$$

We recursively estimate $\omega(n)$ which is the set of coefficients for the desired response matching with iteration index n. LMS receives feedback from $e(n)$ (error between the current noise cancelation filter mapping and the desired response), and updates the next iteration based on Equation 1. The Figure 1 shows the block diagram for the Active Noise Cancellation [15] method.

Due to the lack of a ground truth for the Inter-Beat Interval (IBI)/Heart Rate (HR) signal for our dataset, we evaluate the above methodology on the publicly available TROIKA dataset [16]. This dataset contains a collection of PPG and Accelerometer data along with ground truth ECG in an exercise environment. We evaluated this Active Noise Cancellation and prediction methods on the TROIKA data and obtained an absolute error of 12.1% and a relative error rate of 8.9% for Heart Rate estimation.

Consequently we apply this methodology to our dataset to estimate a continuous Inter-Beat-Interval signal. With the filtered BVP signal, we detect the R-peaks that are above 50% of the BVP signal amplitude. For each detected consecutive R-peak pair, we calculate the time difference between them and detect any variation along the entire BVP

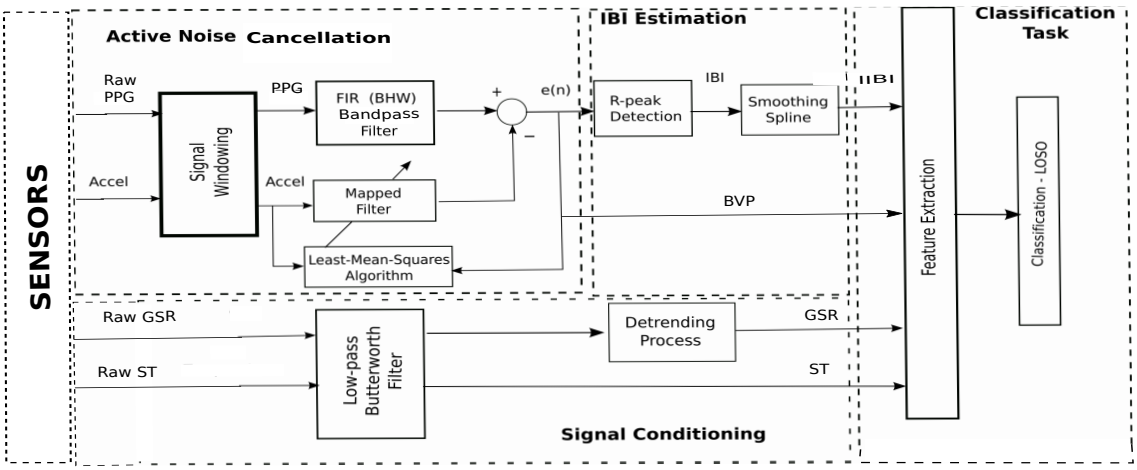

Fig. 1: Pipeline for Hypertension prediction from Wearable Devices. We define four different blocks, Active noise Cancellation based on LMS, R-peak IIBI estimation analyzing the decontaminated PPG, GSR and ST signal conditional and final Classification task stage.

signal. When we detect a new R-peak according to the above criterion, we update the inferred IBI value. Finally we run a smoothing spline algorithm to fix the resultant IBI signal and avoid undesirable harmonics related to IBI discontinuities. This signal is commonly called interpolated-IBI (IIBI) [14]. We can see both these signals in figure Fig. 2.

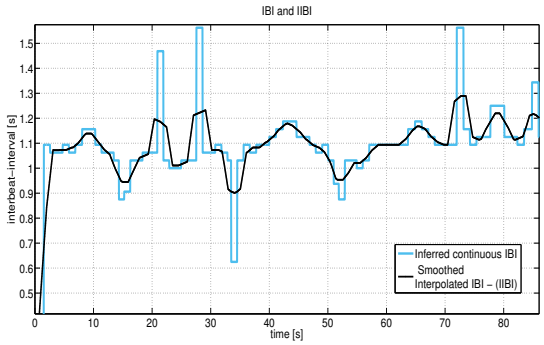

Fig. 2: Example for inferred IBI and Smoothed IIBI.

B. Feature Extraction and Classification

1) Feature Extraction: We experiment with different window sizes to discover the optimal window for continuous monitoring of physiological signals and how the performance varies. Our feature extraction window sizes range from 15 minutes to 2 and a half hours. We extract features from the preprocessed GSR and Skin Temperature signals, and the BVP and IIBI signals derived from the PPG data. Here we discuss the various features extracted from the individual physiological signal streams.

From the Galvanic Skin Response we extract statistical features (mean, SD, min and max) for each session. We also extract the counts of the startle responses (instantaneous changes in response to external stimuli) of the GSR signal and their average rise and fall durations. The duration and amplitude of a the startle response of the Galvanic Skin Response has been shown to be highly correlated with sympathetic activation of a person, and its long term monitoring can be useful in detecting subjects who may be hypertensive . In total we extract 24 features from the GSR signal. We further extract 17 more features form the cleaned Blood Volume Pulse Signal and 8 features from the Skin Temperature Signal.

From the Interpolated Inter-Beat Interval (IIBI) we extract 17 features from the time and frequency domain. The time domain features of IIBI are related to the parasympathetic and sympathetic baroflex function and hence are indicative of Heart Rate Variability. Hence, we extract the maximum and minimum of Heart Rate, RMSSD (root mean square of the successive difference of NN interval), SDNN (Standard Deviation of the NN interval), pNN50 and pNN30 (percentage of consecutive NN intervals which differ by more than 50 and 30 milliseconds respectively). We also derive frequency domain features as indicated in [17], [18]. These features are related to the sympathovagal balance index and indicative of sympathetic and parasympathetic neural activity. We also extract the ratio of the Low Frequency and High Frequency values (LF/HF ratio), and the statistical features given by each frequency range, (e.g. LF and HF: mean, variance, max and min peaks).

2) Machine Learning: For distinguishing between hypertensive and normotensive subjects, we perform a Leave One Subject Out (LOSO) cross-validation classification. Since each test fold contains instances from either a hypertensive subject or a normotensive subject, we compute the final global confusion matrix by combining the individual classes per fold for each subject.

True Positive comprises of all hypertensive subjects classified as hypertensive. True Negative comprises of all the normotensive subjects classified as normotensives. False Positive is all normotensives classified as hypertensives, and all the hypertensives classified as normotensives makes up the False Negative class.

We perform classification with both individual and combined signal streams. A feature-level fusion of the different physiological signal streams is done before running different classification tasks. We perform feature normalization to scale all features to the range [0,1]. We evaluate the performance of five different classification algorithms: K-Nearest Neighbours, Naive Bayes, Decision Trees, SVM

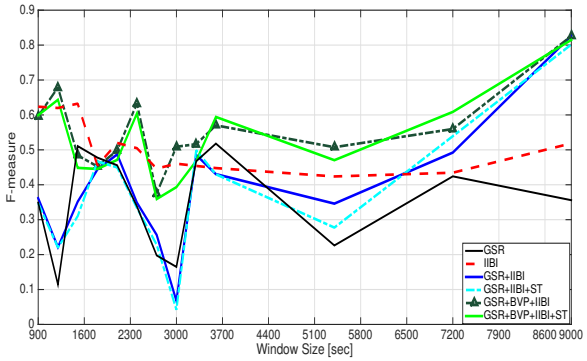

Fig. 3: Effect of the different sampling window sizes (in seconds) for the Adaboost classifier for different Feature combinations.

with Linear kernel, and two ensemble learning algorithms - Adaptive boosting and Random Forest. The ensemble based classifiers outperform the other classifiers for both individual and fusion of features, with Adaptive Boosting performing the best. Adaptive Boosting (Adaboost) is a meta-learner that uses greedy search on a linear combination of weak classifiers to generate a single composite strong learner. We use AdaBoostM1 which is a binary classification algorithm.

When considered separately, individual signal streams have low classification accuracies, with Blood Volume Pulse having the highest F-measure of 0.62. However, combination of features of different signal streams significantly improves the classification results. GSR-IIBI and GSR-BVP-IIBI combinations providing the best discrimination between hypertensive and normotensive subjects. We observe that we are able to achieve a high F-measure of 0.83 using a combination of features from the BVP, GSR and IIBI signals.

The length of the feature extraction windows as discussed in section III-B.1, affect the classification results. Classification results also improve with increase in the signal window. We can see this effect in figure Fig 3.

Table I summarizes the best performance results which are obtained for a 9000 seconds (two and a half hour) window for the various classifiers.

SIGNAL	Adaboost	RandomFor	SVM
BVP	0.62	0.64	0.59
GSR	0.36	0.44	0.25
IIBI	0.52	0.49	0.33
ST	0.50	0.55	0.53
BVP+GSR	0.52	0.60	0.41
BVP+IIBI	0.63	0.56	0.51
BVP+ST	0.68	0.65	0.59
GSR+IIBI	**0.83**	**0.78**	0.59
GSR+ST	0.48	0.41	0.27
IIBI+ST	0.57	0.52	0.50
BVP+GSR+IIBI	**0.83**	0.72	0.60
BVP+GSR+ ST	0.64	0.53	0.40
BVP+IIBI+ST	0.57	0.57	0.42
GSR+IIBI+ST	0.80	0.71	**0.67**
GSR+BVP+IIBI+ST	0.81	0.76	0.63

TABLE I: Classification Results (F-measure) for the three best classifiers for different signal combinations for LOSO evaluation for 9000 seconds (2 and a half hour) window. The best performance for each classifier is marked in bold.

IV. Conclusion

In this study we design and train a complete signal processing and classification system for early hypertension prediction by using non-invasive wearable devices. We construct a robust signal processing methodology for IIBI estimation under real-life scenarios. We demonstrate that the proposed computational pipeline which combines several individual signal streams is able to distinguish between hypertensive and normotensive subjects with high accuracy.

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