# Virtual Cuff: Multisensory Non-Intrusive Blood Pressure Monitoring

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## ABSTRACT

A key challenge in wearable health systems is obtaining continuous blood pressure (BP) information, bypassing intermittent and intrusive cuff inflation. In this paper, we explore the fusion of heterogeneous sensors, notably electrocardiogram (ECG) signals and photoplethysmogram (PPG) pulse oximeter readings, along with activity and location information, for blood pressure information classification and continuous monitoring. We present the Virtual Cuff prototype, a wireless body sensor network for continuous cuff-less blood pressure monitoring, which we use to validate the BP classification approach. The experimental results demonstrate that with over 200 test segments and four BP classes over 86.1% accuracy in classification can be achieved with the Virtual Cuff.

## Keywords

Body Area Networks, Blood Pressure (BP), ECG, Pulse Oximetery, Sensor Fusion, Wireless Health, Wearable Computing.

#### **1. INTRODUCTION**

One of the distinct challenges in pervasive health systems today is capturing continuous blood pressure

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(BP) information. Among the large patient population with chronic high blood pressure, monitoring spikes in BP levels can lead to appropriate tailoring of medications. Additionally, classification of patients with 'white coat' hypertension, those people whose BP rises sharply due to the stress of seeing a physician, can be carried out accurately. Thirdly, continuous blood pressure monitoring can enable users to modify their behavior through biofeedback. For example, alerting a person that their blood pressure is going up when they are driving can help people calm down and improve their heath.

Blood pressure is a critical vital sign monitored by health professionals. It is typically measured manually or digitally using an inflatable arm cuff, which mechanically inflates and deflates to determine blood pressure. With this measurement mechanism, variations in blood pressure readings can be caused by factors such as time of day or even posture. The inflation of the arm cuff and its associated disruption and discomfort have prevented widespread continuous and mobile blood pressure monitoring.

Here. the we examine using biosignals photoplethysmogram (PPG) (which measures oxygenation of the blood) and electrocardiogram (ECG) (which measures the heart signal and rate) to estimate systolic and diastolic blood pressure, as first proposed in the medical literature [1][2][3]. Signal characteristics are derived from the synced PPG and ECG waveforms for the BP value estimation. Specifically, systolic BP has been shown to be correlated to the ECG R-peak point distance from the maximum first derivative of the PPG waveform; and diastolic BP has been shown related to the width of PPG waveform [3].

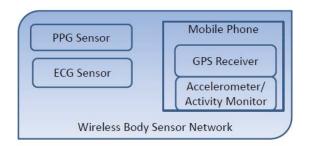


Figure 1. Wireless body sensor network, with PPG, ECG, GPS, and Activity sensors for BP classification.

Contrary to the previous work [1][2][3], all of which work on sedentary data obtained from users who are seated, we examine users in active settings, e.g. walking, running, and biking. The pervasiveness of body sensor networks today requires considering activity in the BP estimation. The value of achieving continuous BP monitoring is dependent on addressing uncertainty and signal artifact that result from movement of the sensors on the body during user activity.

We present our experimental platform, the Virtual Cuff, which fuses data from various sensors, including PPG, ECG, accelerometer, and GPS, for extrapolating BP information, as summarized in Figure 1. A case study using the Virtual Cuff was carried out to examine the experimental validity of the non-obtrusive continuous BP estimation approach, specifically in active settings. We apply Naïve Bayes classification of BP using ECG and PPG characteristics and present the classification results. We further improve the classification of the BP (low, normal, high) using activity data collected from a smart phone tri-axial accelerometer, as well as categorical location data (i.e. in a gym, a park, or a restaurant) leveraging the GPS sensor and the Google Places API.

The main contributions of the paper can be summarized as the following: 1) Developing an approach for BP classification in active settings leveraging PPG and ECG pulse characteristics. 2) Developing a test platform, using off-shelf-components to verify the classification approach, specifically for active users (which is in contrast to the more sedentary users used in the related work). 3) Addressing location and activity based filtering for the Virtual Cuff system, to enhance behavioral cueing.

## 2. RELATED WORK

Continuous and non-intrusive blood pressure monitoring has been identified in the literature as a significant problem in medicine and mobile wearable computing. Invasive approaches to blood pressure monitoring include arterial blood pressure sensors that are inserted via a small catheter inserted into an artery of the arm. Inflatable cuff blood pressure sensors are disruptive and hence not a viable option for continuous BP monitoring.

Non-invasive approaches to continuous BP monitoring have been examined in the literature to varying degrees. First proposed by [1] the pulse interaction characteristics of ECG and PPG signals were explored for BP inference. The authors of [2][3] each developed specialized hardware to experimentally verify the proposition that BP can be inferred from PPG and ECG signals alone. We too build on this work, but with the more challenging and realistic assumption that users can be active, and not just sedentary.

Researchers have looked at comprehensive physiological wearable systems that record a broad range of health signals including PPG and ECG, as in [4][5]. Reciprocally, ECG signal capture and analysis in tightly constrained systems has also been considered extensively in the literature [6][7].

# 3. VIRTUAL CUFF TEST PLATFORM

The Virtual Cuff platform was developed to experimentally examine BP classification using ECG and PPG waveforms in real-time and active settings. The system enabled identification of the signal quality constraints, including the large noise and artifact introduced in its continuous measurements of ECG with the user actively engaged in exercise. The system is enhanced with GPS and activity recognition to further improve the BP classification. Figure 2 provides an overview of the sensor and component interactions of the Virtual Cuff.



Figure 2. Virtual Cuff Sensor and Component Interaction Overview

### 3.1 System Architecture

The Virtual Cuff is composed of off-the-shelf ECG and PPG sensors distributed on the body, with a mobile phone acting as the on-body computational and communication device. The sensor devices, shown in Figure 3, include the Nonin Onyx II fingertip pulse oximeter which retrieves PPG signals and the Zephyr Bioharness that collects (among other signals) ECG data. They both wirelessly connect and transmit data via Bluetooth to the mobile phone gateway. An Android app coordinates the communication between the smart phone and external device sensor data, while also filtering and relaying the data to the cloud.

GPS and activity recognition using the tri-axial accelerometer are used to enhance the accuracy of the inferred BP values and relevance of the behavioral cues given to the users. Data collected from the sensors is processed in the cloud. Feedback is provided to the user regarding their estimated blood pressure classification via the smart phone app, shown in Figure 3c.



Figure 3. Virtual Cuff Sensor and Interface. a) Nonin Onyx II 9560 Fingertip Pulse Oximeter used on the finger to derive PPG signals. b) Zephyr Bioharness strapped to the users chest collects ECG data. c) Screen Shot of Android App

### 3.2 Activity and Location-Aware Filtering

Classification of the BP signal was carried out for the biofeedback. Specifically, a low, normal, high blood pressure alert cue was provided, taking into consideration activity and categorical location. For example, locations of high activity coupled with high BP values (as in exercise in a gym) were filtered out during behavioral cueing.

The classification of activities (e.g. walking, sitting, climbing stairs, driving) uses the mobile phone's accelerometer. The location of the user is obtained with the phone's location services, including GPS and cellular network based localization. The last registered

location within a five minute window was used, for scenarios where the GPS signal is absent and the cellular network based approach is also compromised. The Google Places API was used to determine the type of establishment of the high blood pressure incidence. Location types including gym, park, and restaurant can be obtained with a geocode (i.e. longitude and latitude).

## 4. CLASSIFICATION VALIDATION

## 4.1 Experimental Set-up

The Virtual Cuff was used in a series of 260 test segments with a participant either walking (low activity), climbing stairs (low/medium activity), bicycling (medium/high), and running (high), while attempting to maintain a constant heart rate.

In 12 of the tests (3 with each activity), once the activity was completed a blood pressure cuff was attached to the participant's arm and blood pressure was measured. The average BP (systolic and diastolic) readings, given in Table 3, along with the average pulse readings, were recorded.

The blood pressure readings were taken with an Omron Automatic Blood Pressure Cuff, which calculates the BP by averaging several samples calculated with single inflation and deflation of the cuff. Hence some delay is introduced in the time the inflatable BP sensor takes the BP measurements.

Table 3. Blood pressure and pulse readings recorded using a standard extrinsic blood pressure cuff.

Activity Level	Systolic BP	Diastolic BP	Pulse
Low	126	62	54
Med/Low	148	76	129
Med/High	184	96	157
High	251	87	163

In the experiments, the ECG signal packets were updated every 4ms with a frequency of 25 MHz. The R-to-R data points, based off the ECG waveform, register every 55ms, with a frequency of 18 mHz. A separate R-to-R transmitted value was used for verification of the ECG signal rate. The PPG data's pleth values appear as bundles every 13ms with a frequency of 75 per second. The accelerometer updates every 50ms and the GPS is set to update with every 10 meters and/or 500ms.

The Zephyr BioHarness, in addition to ECG signal packet every 250ms, also updates the heart rate, the breathing rate, and the temperature every 1ms.

#### 4.2 **Experimental Results**

The time series data collected for bicycling and climbing stairs were greater in length than others, and so all the signals from all the activities were split into equal segments, resulting in a total of 260 segments total, with more segments for some activities.

Dia2 and Sys\_tl values were extracted from the experimental results, and using those sets of data as well as the directly measured blood pressure data, a prediction model using the Naive Bayes Classifier was created. The prediction matrix is provided in Table 4.

Table 4. Predication matrix for the Naïve Bayes Classifier for experimental data extracted from the Virtual Cuff system.

Prediction Matrix							
Activity		Original Class					
			Low/	Med/			
		Low	Med	High	High		
	Low	81.8%	0%	0%	6.4%		
Recognized Class		(18)	(0)	(0)	(8)		
	Low/	0%	93.7%	12%	0%		
	Med	(0)	(59)	(6)	(0)		
	Med/	0%	6.3%	60%	0%		
zing	High	(0) (0)	0.3% (4)	(30)			
eco	High	18.2%	0%	28%	93.6%		
R		(4)	(0)	(14)	(117)		

Table 4 shows that the model can classify with errors. Of the 260 segments, 224 segments were accurately classified in terms of their blood pressure readings, i.e. low, low/med, med/high, or high. Three out of the four of the classes were classified with over 80% accuracy across 210 segments. The Med/High class, which experienced the highest error in classification, was incorrectly classified as High BP in 14 test segments and as Low/Med BP in 6 test segments. With an overall false positive rate of just under 14%, the approach is a positive confirmation of the feasibility of continuous, nonintrusive blood pressure monitoring with coarsegrain blood pressure classification.

## 5. CONCLUSION

The Virtual Cuff continuous blood pressure monitoring system, with BP classification for behavioral cueing was presented. Leveraging non-invasive and non-intrusive sensors, specifically ECG, PPG, GPS, and Activity sensors, the system is able to classify the user's blood pressure with over 86% accuracy. The approach was also validated on data collected using our Virtual Cuff platform.

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