

# Machine Learning Oriented Effective Monitoring Of BP and Heart Beat Using ECG or Photoplethysmography

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**ABSTRACT :** In this paper, we propose a completely ear-worn long haul circulatory strain (BP) and heart rate (HR) screen to accomplish a higher wearability. Additionally, to empower handy application situations, we show a machine learning system to manage extreme movement ancient rarities instigated by head developments. We recommend arrange all electrocardiogram (ECG) and photoplethysmography (PPG) sensors behind two ears to accomplish a super wearability, and effectively get rarities affected signs. Moreover, we propose an unsupervised learning calculation frail ear-ECG/PPG signals utilizing a semi-altered stage. In the wake of presenting head movements towards, we apply a bolster vector machine classifier to take in and distinguish crude heartbeats from movement ancient to consequently sift through remaining misshaped/faking heartbeats, for ECG-to-PPG beat travel time (PTT) and HR estimation. In particular, we present a dynamic time twisting based learning way to deal with evaluate contortion states of crude heartbeats alluding to a great pulse design, which are then contrasted with an edge with perform purging. The pulse design and the contortion limit are found out by a K-medoids grouping approach and a histogram triangle technique, individually. A while later, we play out a near examination on ten PTT or PTT&HR-based BP learning models. In view of an obtained dataset, the BP and HR estimation utilizing the proposed calculation has a mistake of  $-1.4 \pm 5.2$  mmHg and  $0.8 \pm 2.7$  beats-per-minute, separately, both much lower than cutting edge approaches. These outcomes show the capacity of proposed machine learning-engaged framework in ear-ECG/PPG procurement and movement tolerant BP/HR estimation. Importance: This confirmation of-idea framework is relied upon to represent the achievability of ear-ECG/PPG-based movement tolerant BP/HR checking.

**KEYWORDS:** Blood pressure, Heart rate, Photoplethysmogram, Hardware prototype, Data collection, Signal Acquired

## I. INTRODUCTION

HIGH blood pressure (BP), also called hypertension, is a common but dangerous condition, impacting over 35 percent of people, relating to many cardiovascular, circulatory and cerebrovascular diseases, and causing 12.8 percent of total deaths worldwide [1]. Long-term BP monitoring is a key factor in hypertension control for several reasons. Firstly, hypertension is often associated with few or no symptoms which makes timely early diagnosis and treatment highly challenging without daily BP tracking. Moreover, a frequent BP measurement is significant to check up how well the treatment of hypertension is going on. Besides, BP always fluctuates over time, making the measurement at specified times and circumstances insufficient for effective BP monitoring and analysis. However, the traditional BP measurement methods usually cannot well fit the needs of long-term application scenarios, such as the invasive catheterization method sacrificing the comfortableness and the noninvasive cuff-based oscillometry approach lacking of a good wearability [2].

Wearable computers are paving a promising way for pervasive smart health wearables for people around the world, especially for developing worlds where major problems include lack of health infrastructure and limited health coverage. Wearable computers can provide health management in a more affordable manner than traditional health services, especially when long-term continuous health data collection is needed for effective diagnosis/treatment of chronic diseases like hypertension.

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In the proposed machine learning-based framework, we firstly try to identify the raw heartbeats using our previously reported support vector machine (SVM)-based approach [1]. Afterwards, to filter out many residual distorted or faking raw heartbeats, we further propose an unsupervised learning approach to automatically label the heartbeat quality levels and purify the raw heartbeats. Specifically, we introduce a dynamic time warping (DTW)-based learning approach [3] which can perform non-linear mapping of two time-varying sequences, to measure the dissimilarity between each raw heartbeat and a high quality heartbeat pattern.

## II. RELATED WORK

Circulatory strain checking in view of heartbeat travel or entry time has been the concentration of much research with a specific end goal to outline wandering pulse[1] screens. The precision of these screens is constrained by a few difficulties, for example, securing and preparing of physiological flags and also changes in vascular tone and the pre-discharge period. In this work, a writing study covering late improvements is exhibited to distinguish crevices in the writing. The discoveries of the writing are ordered by three angles[3].

These are the adjustment of heartbeat travel/landing times to circulatory strain, obtaining and preparing of physiological signs lastly, the plan of completely coordinated pulse estimation frameworks. Elective innovations [5] and additionally areas for the estimation of the beat wave flag ought to be examined with a specific end goal to enhance the precision amid adjustment. Moreover, the joining and approval of observing frameworks should be enhanced in current walking circulatory strain screens.

## III. METHODOLOGY

### A. System Overview

The proposed machine learning-enabled system is illustrated in Fig. 1. The top part (Fig. 1a) gives the customized hardware prototype and the sensors placement method for ear-ECG and PPG signals acquisition. The bottom part (Fig. 1b) shows the flow of the signal processing and HB/SBP estimation algorithm including three stages, i.e., stage I – supervised learning of heartbeat (HB) identification, stage II – unsupervised learning of signal quality labelling and signal purification, and stage III – HR estimation and supervised learning of SBP estimation. The proposed algorithms can be run on the mobile devices such as cellphones. Therefore, no computation resources will be introduced to the wearables and the form factor will not be increased. One thing worth noting is that the ML-based algorithms are expected to deal with large amounts of motions artifacts in daily applications, which is very challenging but necessary to enable 24-hour continuous blood pressure/heart rate tracking.

The below figure shows the customized hardware platform. The components are :

**Signal Acquired :** This is the first step where all the required signals are been acquired as input.

**Data collection :** This is the second step where the data is collected according to the signal acquired.

**Hardware prototype :** This gives the hardware required for the processing of the signal and the data collected from the above two steps.



The customized hardware platform shown in Figure above includes two parts, i.e., the ECG and PPG subsystems. In the former one, the ECG signal is acquired by an ADS1299 24-bit analog-to-digital (ADC) with a sampling rate of 500 Hz on a TI ADS1299EEG-FE evaluation board (green one) [2] and is then sent via the SPI port to a TI TivaTM C

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series LaunchPad (red one) [3], which is equipped with an ARM Cortex M4 microcontroller to configure the ADC and relay the signal to a PC via the USB port. In the latter one, the PPG signal is acquired by a 22-bit ADC with a sampling rate of 128 Hz on a TI AFE4490SPO2 evaluation board [2], which also owns an MSP430F5529IPN microcontroller to configure the ADC and relay the data to the PC.

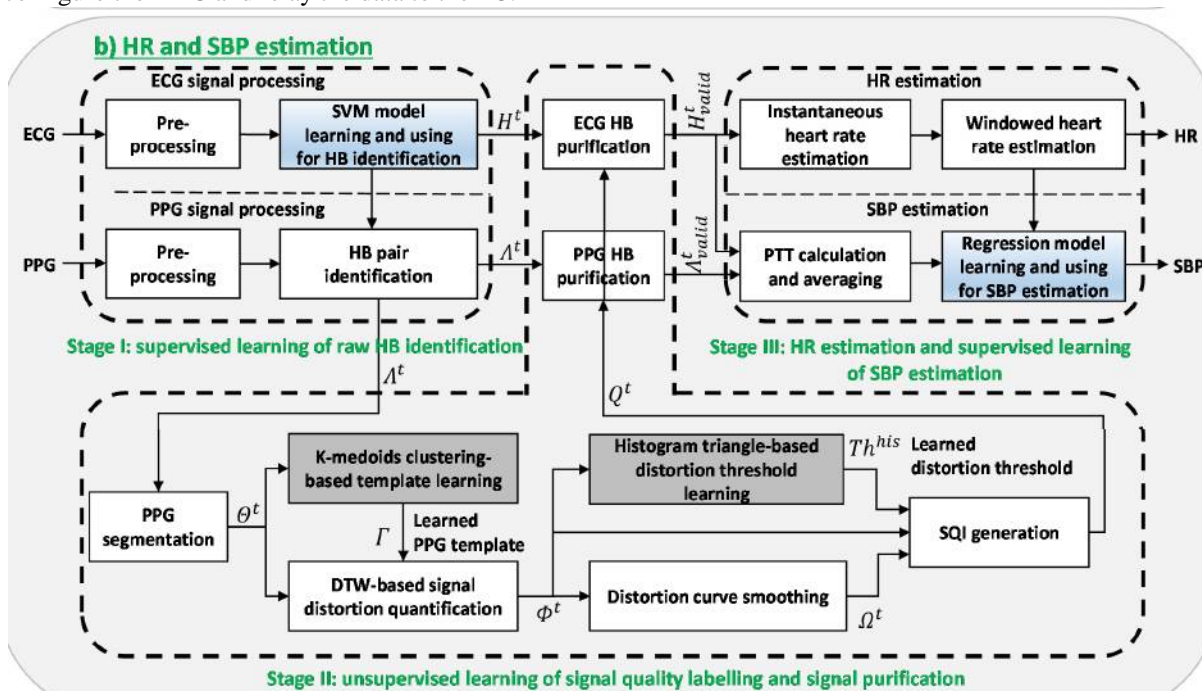


Fig. 1. The proposed machine learning-enabled system for wearable cuff-less SBP and HR monitoring from motion artifacts sensitive ear-ECG/PPG signals. Algorithm block coloring in b): white colored blocks are active in both training and testing phases; each blue colored block include both a supervised model learning process and a model using process, which are active in the training phase and the testing phase, respectively; each gray colored block includes an unsupervised model learning process and is active only in the training phase.

The above figure explains the HR and SBP estimation. This component contains ECG processing. A higher sampling rate for ECG is based on the consideration that it is used for both HR and PTT estimation. This prototype can be conveniently used in long-term applications after removing evaluation-specific components and adding a wireless module. The sensors placement method proposed is illustrated in the top right part of Fig. 1a, where the R/B/S correspond to the reference/bias/signal electrodes for single-lead ECG acquisition, and P represents the sensor for PPG measurement. All the sensors can be integrated into glasses or ear headsets to achieve a much higher wearability and comfortableness, compared with the chest or wrists placement.

## B. Signal Pre-processing

The raw ear-ECG and PPG signals are both processed by a six-order Butterworth bandpass filter (2-30 Hz and 0.5-8 Hz, respectively). Then PPG is resampled to 500 Hz to obtain a same time resolution as ECG. An example of acquired ear-ECG and PPG signals with only background motion artifacts is given in Fig. 2, where clear signal morphologies can be observed. More analysis about the signal quality with deliberately introduced severe motion artifacts will be given later. ECG-based and PPG-based Heartbeat Identification : To identify raw heartbeats from weak ear-ECG signal impacted or corrupted by large amounts of background and deliberately introduced motion artifacts, our previously reported SVM-based approach is applied. Specifically, after segmenting the ECG stream to heartbeat candidates by an adaptive threshold-based auto-segmentation approach, ten critical multi-domain features are extracted from each candidate and fed into the SVM classifier for raw heartbeat identification. The SVM model is learned based on the ear-ECG training data and tested on the ear-ECG testing data for each subject. The heartbeat locations from the

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chest-ECG stream collected at the same time are used as reference to label whether the ear-ECG heartbeat candidates are real heartbeats or motion artifacts-induced interferential spikes, to enable a supervised learning process. The SVM decision function is presented by (1), where  $\mathbf{x}$  is the ten-dimensional input vector,  $\mathbf{w}$  is the support vector insupport vectors learned and is its class label,  $b$  is the weight learned,  $b_0$  is the bias learned, and  $\gamma$  is the kernel which is chosen as a linear one to lower computation load in wearable applications. Based on the raw ECG heartbeats, the raw PPG heartbeats (PPG feet) can be determined by searching the minimum points between each two adjacent R peaks [2].

## C. K-medoids Clustering-based Template Learning

As mentioned above, a PPG heartbeat template with a good morphology is needed by the DTW algorithm, to screen the raw PPG heartbeats to calculate their distortion values used in signal quality labelling. However, there is no pre-labeled signal quality information to directly perform PPG template selection, otherwise, it is unnecessary to perform the unsupervised learning of signal labelling in the proposed system.

Algorithm:

### Input:

raw PPG HB locations in T trials  $A^t, \forall t \in [1, T]$

raw ECG HB locations in T trials  $H^t, \forall t \in [1, T]$

number of centroids in K-medoids clustering K

number of points used in distortion smoothing S

shrinkage factor used in distortion threshold learning  $d$

lower limit of percentage of HBs to be protected  $p$

step size in percentage to adaptively adjust the threshold  $n$

### Output:

Heartbeat signal quality indices in T Trails

Valid PPG HB location

Valid ECG HB location

### Procedure:

For  $t=1$  to T do

$O = \text{PPG segment split by } A^t$

If  $t=1$  then

$L = \text{average length of segments in } O$

$O = \text{all segments in } O \text{ resampled to a length of } L$

Else if

$Q = \{\Delta_j^t \mid \Delta_j^t = \text{DTW}(O_j^t, p, n)\}$

End for

For  $t=1$  to T do

$M^t = \text{smooth}(Q^t, S)$

$A_{\text{valid}}^t = \text{PPG HBs validated by } A^t$

$H_{\text{valid}}^t = \text{ECG HBS validated by } A^t$

End for

## IV. RESULTS

### A. Heartbeat Identification

Firstly, the ECG signal acquired with the non-standard signal lead configuration is so weak that it is continuously impacted by the background motion artifacts due to uncontrolled neck muscle and blood vessels movements, as shown in Fig. 5. Specially, in the signal periods not covered by the wide orange rectangles, the PPG signal owns a better signal



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morphology compared with the ECG signal, which is even highly corrupted by the background motion artifacts such as the segment in the narrow orange rectangle in Fig. 5a). However, as shown in the wide rectangle (corresponding to deliberately introduced head movements) in Fig. 5a, the ECG signal actually owns a relatively better motion artifacts tolerant ability than the PPG signal leveraging sharply changing QRS complexes, although the ECG signal is weaker than the PPG signal.

Therefore, we firstly perform raw heartbeat identification from the ECG signal. Secondly, the PPG signal is highly distorted in the wide orange rectangles due to deliberately introduced motion artifacts by head movements, as shown in wide rectangles in Fig. 5a-b. Since PPG heartbeat morphological characteristics (PPG feet) during these signal periods cannot reflect the heartbeat occurrence time for PTT calculation, we need to filter out these signal segments according to the signal quality of these raw PPG heartbeats.

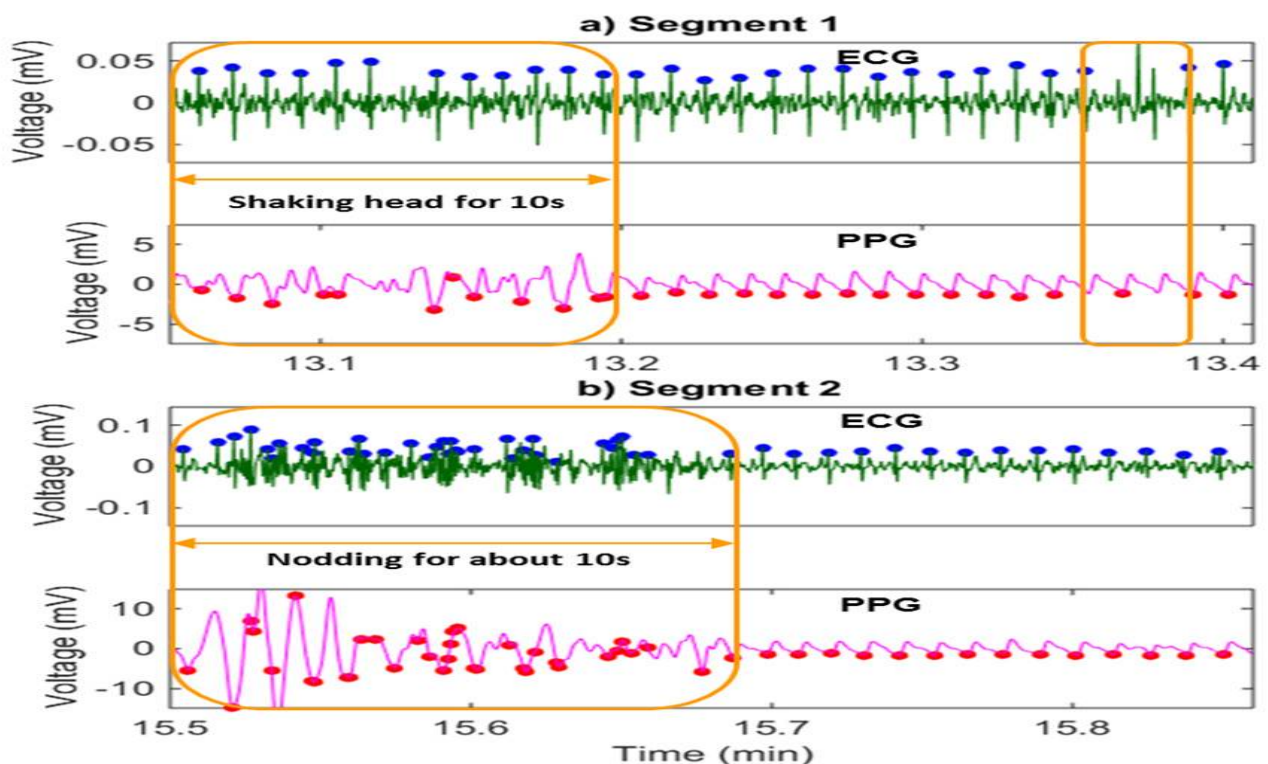


Fig. 2. Two examples of heartbeat identification results in the testing session of the subject 1. Blue dots: identified raw ECG heartbeat locations; red dots: identified raw PPG heartbeat locations; wide orange rectangles: signal periods with deliberately introduced motion artifacts due to head movements; narrow orange rectangle: signal period with missing or fake heartbeats due to severe background motion artifacts; all the weak ECG signal is continuously impacted by background motion artifacts.

## IV. CONCLUSION

In this paper, we propose a fully ear-worn system to provide a high wearability for long-term cuff-less blood pressure and heart rate monitoring, and further present a machine learning-based signal processing framework which owns a high motion-tolerant ability to enable daily applications. Firstly, we proposed a sensor placement approach to meet the critical requirements on the wearability and comfortableness, which allows for situating all sensors behind two ears and the possibility to integrate them into glasses or ear headsets. We successfully acquired the weak ear-ECG and ear-PPG signals with our semi-customized bio-potential acquisition platform, and explored diverse background and head movements-induced motion artifacts towards practical application scenarios.

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