A Photoplethysmograph Based Practical Heart Rate Estimation Algorithm for Wearable Platforms

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ABSTRACT

We propose a practical Heart Rate Estimation algorithm utilizing wrist-based photoplethysmography (PPG) signals for continuous health monitoring of crane workers who spend long hours in an isolated cabin in the harsh factory environment. Our novelty lies in devising a low footprint algorithm that can reliably estimate Heart Rate in presence of motion artefact as well as offers the feasibility of deploying on a wearable platform. More particularly, our solution addresses two fundamental issues: *a*) correcting weak wrist PPG signal from frequent motion artefacts and *b*) identifying signal processing techniques that can be practically implemented on an embedded platform with limited resources in terms of memory and CPU. Experimental results demonstrate the validity of such algorithm and exhibit a great potential to be employed in the real field.

Keywords

Photoplethysmography (PPG), Heart Rate Monitoring, Motion Artefact, Random Forest, Practical Wearable Computing

1. INTRODUCTION

The crane operators in a steel factory are subjected to the adverse condition and exposed to wide variety of hazardous substances. Moreover, they suffer from continuous physical and mental fatigue due to the confinement in an isolated cabin under harsh environment [3]. Although various safety measures are employed, still no continuous health monitoring is available to ensure the operator's safety while they are operational. Moreover, since they are involved in transporting molten metals, any misoperation could lead to catastrophe in the factory site. Hence, continuous monitoring their health is a matter of the utmost importance to foster a safe factory environment. Unfortunately, one cannot attach multiple medical devices to them as it is not feasible as well as not practical. However, recent advancement in wearable health devices motivated us to devise a solution based on sensing one's PPG signature that directly carries Heart Rate (HR) information. It is to be noted that even only monitoring HR and Heart Rate Variability (HRV) information can provide vital health signatures and can be leveraged to desist any emergency condition. Thus, we propose to continuously measure the PPG signal and chose wrist-based PPG sensors for complete unobtrusive usage. However, practically the proposed solution is far more complex than it sounds as: *a*) the wrist PPG (compared to usual finger-tip PPG) is an extremely weak signal, *b*) crane workers are always in motion while handling the levers that in turn introduces lot of motion artefacts in the PPG signal, *c*) the crane cabin has lots of environmentally coupled vibration to further affect the PPG adversely, and *d*) the embedded wearable platform doesn't allow complex denoising algorithm due to limited resources.

In prior works, we found a myriad of research papers proposing signal processing techniques to correctly estimate HR from motion contaminated wrist PPG signals. Several of them implement the adaptive filtering techniques [4], Singular Spectrum Analysis (SSA) [8], independent component analysis (ICA) [5] and wavelet based method [6] to estimate the heart rate in presence of motion. Among those, two notable methods are CARMA [2] and TROIKA [8]. TROIKA is a framework that exploits Singular Spectrum Analysis(SSA) based decomposing method to partially remove the motion artefact components. Furthermore, Sparse Signal Reconstruction (SSR) is deployed which yields the high resolution spectrum analysis and estimates the heart rate eventually. CARMA [2] is another interesting approach which eliminates the motion artefact by analyzing the frequency of PPG and accelerometer eigen vectors obtained from SVD. Though the prior arts provide very efficient heart rate estimation algorithm, majority of them were analysed offline due to their computational complexity. Hence, they cannot be deployed to resource constrained wearable devices/platforms.

Acknowledging these issues, we propose an algorithm that can run on a wearable platform and yet provide real-time reliable HR measurement from weak wrist PPG in presence of frequent and large motion artefacts. Our algorithm ex-

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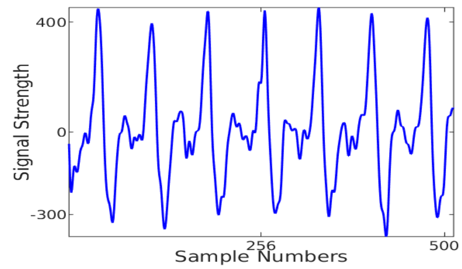
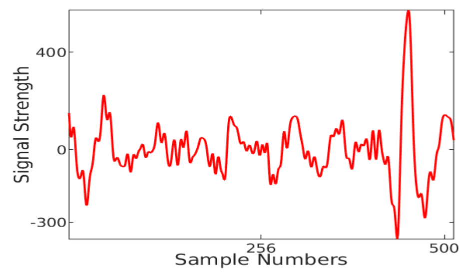
ploits the accelerometer signal and utilizes the Random Forest Classifier to find the peak associated with cardiac rhythm in presence of multiple candidate peaks in the resultant PPG spectrum.

In pursuit of simulation for real time scenarios, a visit to the factory site was carried out to observe the operational activities performed by a crane operator. The major activities which encompass the work schedule of the crane operator are as follows: *a*) continuous steering of the crane lever for hoisting heavy vessels, and *b*) communicating with the supervisor using walkie-talkie who sits at the base station and controls the whole operation. Accordingly, we have designed and simulated the experiments aligned to the above mentioned activities in a lab environment. Later the algorithm is validated against the collected lab dataset. The paper is organized as follows: Section 2, highlights the research overview and challenges involved in estimation of heart rate from motion contaminated PPG signal. Next, Section 3 describes the algorithm components in detail and addresses the design principle. This is followed by Section 4 which provides the experimental design and results to evaluate, the performance of various algorithmic components. Finally, the paper summarizes the efficacy of the algorithm and draws an outline of further research pertaining to this topic.



(a) Static PPG Signal



(b) Motion Contaminated PPG Signal

Figure 1: Motion Contaminated PPG Signals

2. RESEARCH CHALLENGES

Inherently, PPG signal [1] contains a slowly varying periodic signal associated with cardiac rhythm. The periodicity represents the heart rate. However, quality of PPG signal is drastically degraded due to the motion artefacts during physical activities (as depicted in Figure 1). Hence, reducing the motion artefacts and estimation of accurate heart rate from PPG signal becomes a challenging problem. Particularly, the motion artefacts are not easily avoidable when frequency overlapping occurs between motion artefacts and heart rate. Thus, general frequency domain filtering methods are unsuccessful to minimize the motion artefact, more sophisticated techniques need to be adopted to estimate the heart rate from PPG.

3. METHODOLOGY

The following section describes the methodology and various algorithm components of the system. The flow chart representation of the complete algorithm is illustrated in Figure 2. The detailed description of the various components are described below:

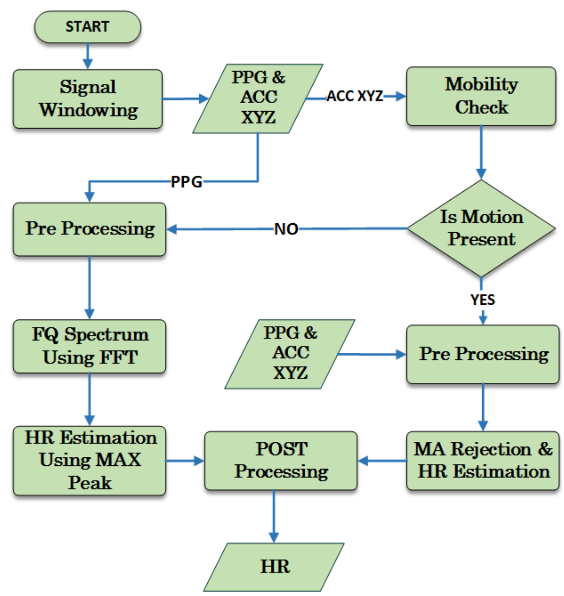


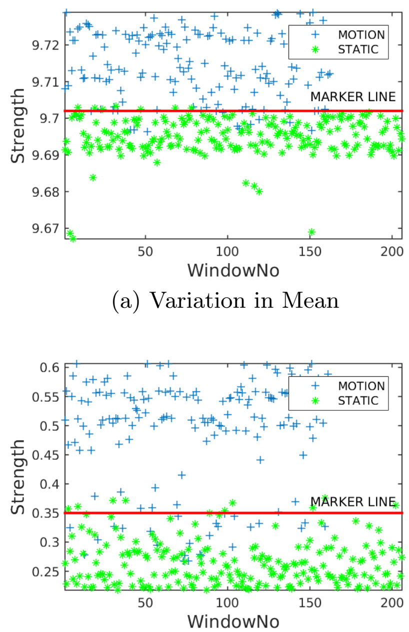
Figure 2: Flow Chart of the Algorithm

3.1 Signal Windowing

Estimation of the heart over the longer time period with higher sampling rate imparts higher accuracy. However, this approach is not feasible for the wearable system due to the limited memory print and computational overhead. Considering the memory constraint, the time window is chosen optimally to 10 seconds and the sampling rate is fixed to the minimal sampling rate of 50Hz available for the PPG sensor. Raw PPG and accelerometer data are acquired simultaneously with fixed sampling rate which imposes time synchronization.

3.2 Mobility Check

Mobility check algorithm is applied to the raw time series of accelerometer data to determine the mobility or static phase. The system imposes different algorithm for static as well as the mobile phase to increase the efficacy of the system. In accordance with the feasible system, we implement a modest yet a robust algorithm, incorporating statistical features and decision tree based technique to determine the motion in a particular time window. Decision tree is very efficient and familiar tool for classification and prediction. It caters different rules, constructed in top-down manner and can be implemented easily. According to the analysis, while in motion the resultant value of the 3 axis accelerometer is increased significantly compare to the static mode. This variation is captured in the form of mean and standard deviation of a time window of the resultant accelerometer (as depicted in Figure 3).



(a) Variation in Mean

(b) Variation in STD

Figure 3: Variation in Mean and Standard Deviation

For every time window, the mean and standard deviation of the resultant of 3 axis accelerometer are denoted as feature and mobility flag represents the class. Numerous such windows are fed to the offline training and a model decision tree (if else ladder) is deployed for reliable estimation of the motion for a window.

3.3 Pre-Processing

In general, every biological signal is constricted to a range of frequencies. The range in case of a heart signal, spans from 0.75Hz to a maximum 3Hz, which encompasses the heart beats per minute (BPM) from 45 BPM to 180 BPM. Therefore, the raw PPG signal is subjected to the band pass filtering with mentioned frequency range. The filtering process eliminates the respiratory signal as well noise and motion artefact outside of the frequency band of interest. As the filtering phase introduces a phase distortion to the signal, zero phase digital filtering is opted to remove the phase distortion and retain the original shape of the signal. Zero phase digital filtering implements the forward and reverse filtering. Considering the real time implementation, IIR filter (direct form II type) is opted for filter realization.

3.4 HR Estimation Using Frequency Analysis

As explained earlier, the periodicity in PPG signal is associated with the cardiac rhythm. Thus finding the fundamental frequency leads to the estimation of heart rate. This is accomplished by performing Fourier Transform on pre-processed PPG signal and identifying the frequency of the highest peak (F_{max}) from the power spectrum. Then the frequency is converted to beats per minute to obtain the Heart Rate ($HR = F_{max} * 60$).

3.5 Motion Artefact Identification and HR Estimation

Essentially, the motion contaminated PPG signal contains the signal component caused by the motion and another signal component contributed by cardiac rhythm. Therefore, the maximum spectral peak of PPG is not always corresponding to the cardiac cycle; it could be associated with the motion. However, as the cardiac rhythm is one of the major contributors of the PPG signal; hence the assumption could be made that if first peak is due to motion then the second highest peak is associated with cardiac cycle. To summarize this, the whole problem is formulated in distinguishing the peak associated with cardiac rhythm among the two highest candidate peaks obtained from the frequency spectrum of PPG. In order to validate the right cardiac peak, we have leveraged the accelerometer signal as it is another independent source which captures the motion artefact. If a significant accelerometer peak is aligned with highest PPG peak, motion contamination is acknowledged and two distinct scenarios are appraised while estimating the heart rate.

- If the power of both accelerometer and second highest PPG peak is relatively small; we have hypothesized that the second highest peak is due to motion and highest peak is associated with HR.
- Conversely, the second highest PPG peak is considered for HR estimation when it attributes the significant amount of power compare to the accelerometer and highest PPG peak.

However, this decision making is not as straightforward. Random Forest classifier is employed for peak selection which is explained in details in Section 3.5.3. This peak ambiguity and different scenarios are illustrated in Figure 5. The process of choosing the heart rate peak consists of three major stages, namely: *i*) Peak Validation using CFAR Algorithm, *ii*) Identifying Peak Alignment and *iii*) Peak Identification Using Random Forest. Flow chart of this process is depicted in Figure 4.

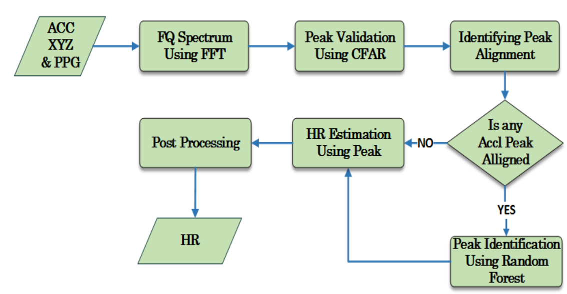
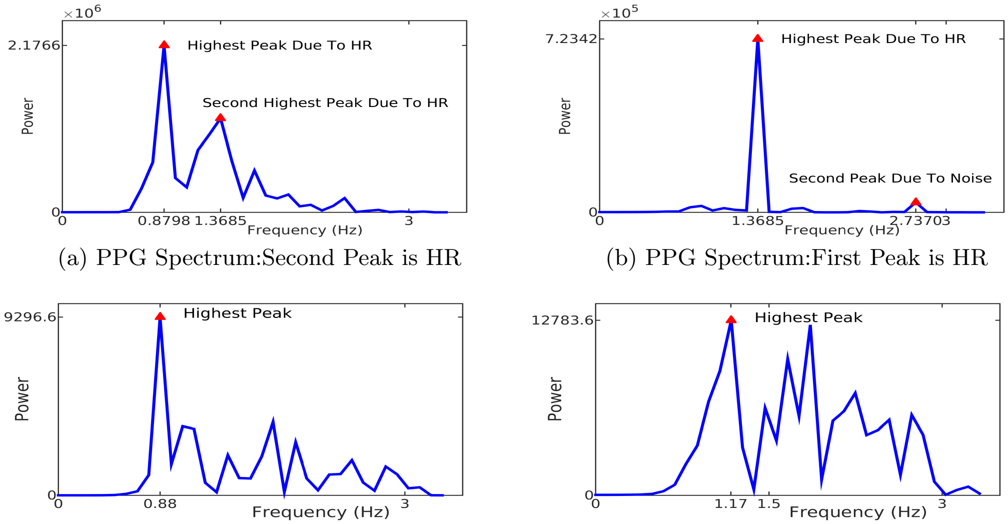


Figure 4: Flow Chart of Motion Artefact Rejection and HR Estimation

3.5.1 *Peak Validation using CFAR Algorithm*

Before considering the Peak Alignment process, the peaks from acceleration spectrum need to be validated as the acceleration signal is very noisy in nature. In order to validate the peaks, CFAR[7] algorithm is adopted to eliminate the noisy spurious peaks while validating the prospective peak in accelerometer spectrum. It is an adaptive detection algorithm to detect the target when the background is varying



(a) PPG Spectrum:Second Peak is HR

(b) PPG Spectrum:First Peak is HR

(c) ACC Spectrum

(d) ACC Spectrum

Figure 5: Two Different Scenarios of Peak Selection

both spatially and temporally and cluttered with random noises. Cell averaging CFAR or CA-CFAR implementation is applied as peak detection algorithm due to its simplicity. The basic principle of CA-CFAR is very straightforward. It compares the peak power with the defined threshold and validates accordingly. The algorithm demands three parameters to be tuned: *i*) Training Cell size (tc), i.e. the no. of sample peaks which are to be contemplated on either side of cell under test (CUT); *ii*) Guard cells size (gc), which is the no. of sample peaks to be ignored on either side of cell under test (CUT) to avoid the corruption in power estimation; and *iii*) Detection Threshold (T). The average power of the peaks are calculated for the training Cell size by the other side of CUT and compared with the detection threshold (T). The average peak power is estimated by the Equation 1.

$$PP_a = \frac{1}{2 \times tc} \left(\sum_{k=i-gc-tc}^{i-gc-1} PP_k + \sum_{k=i+gc+1}^{i+gc+tc} PP_k \right) \qquad (1)$$

Where PP_k is the power of the Acceleration peak at k^{th} sample of the window.
For a particular peak, if PP_k is greater than the detection threshold(T) then it is termed as valid peak. The detection threshold is denoted as $T = \alpha PP_{cut}$. Where PP_{cut} is power of the peak under CUT and α is scaling factor. The scaling factor α is derived heuristically after analyzing various true peaks of accelerometer signal.

3.5.2 Identifying Peak Alignment

As already discussed, the highest peak obtained from PPG spectrum creates the ambiguity whether it is pertaining to cardiac cycles or due to the effect of motion. The major decisive factor is finding a significant acceleration peak aligned with PPG peak with a tolerance range. If the acceleration spectrum contains any such kind of peak then hypothetically, it could be assumed that the acceleration signal has overlapped the heart rate region. Consequently, the two highest peaks of the PPG spectrum need to be considered to determine the actual cardiac peak.

3.5.3 Peak Identification Using Random Forest

Based on the analysis, it is observed that there are three parameters which are the deciding factors for ascertaining the right cardiac peak. The parameters are following: *i*) Power of the first highest peak of the PPG spectrum, *ii*) Power of the aligned peak of the Accelerometer spectrum, *iii*) Power of the second highest peak of the PPG spectrum.Considering these parameters with respect to the peak selection, this problem could be categorized as two class classification problem, where each peak represents one class. Given the parameters, two features is chosen by analysing the mentioned parameters and annotates the right peak as class. Two parameters are as follows:

- The ratio of highest PPG peak power to the power of the acceleration peak aligned with highest PPG peak.
- The reciprocal of second highest PPG peak power.

Considering the feasibility issue, Random forest algorithm is employed as classification algorithm due to the fast predicting response and less complex implementation of the testing phase. Inherently, random forest algorithm integrates various underlying decision trees and predicts the class that is the mode of classes predicted by individual trees. It is an ensemble learning method, grows multiple of little decision trees from random subsets of data. Randomly, each tree predicts the class and final class is obtained by the majority voting. The training phase is accomplished offline and the training model is deployed for further peak classification.

3.6 Post-Processing

Owing to the peak identification algorithm, the right cardiac peak is opted and heart rate is estimated during the motion as well as rest phase. However, the algorithm is not always the perfect and erroneous HR values are introduced due to the various issues. To improve the estimation accuracy of the system, a histogram based post processing method is implied on the set of estimated HR values over the duration for one minute. The entire range of HR values ranging from the lowest value to the highest value is considered and number of bins are created by selecting the bin width of three. Each HR value is placed within a particular bin. The bin that contains the maximum HR values is chosen and median of these HR values is decided as final heart rate. Thus, for every minute one HR is obtained for further analysis.

4. EVALUATION

4.1 Experimental Setup

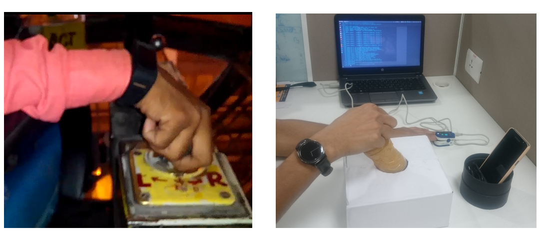
The experiments[1] were conducted in a controlled environment inside a lab, whereby the subjects were asked to wear a smart watch (to record Accelerometer and raw PPG data) and simulate the hand motions of a crane operator in a specific sequence.

4.1.1 Devices Used

A total of 4 devices were used to perform the experiments and are listed as follows:

- **Dummy Crane Lever** is made with a 500 ml mineral water bottle mounted on a rigid support. The lever is free to rotate in 360 degrees at a horizontal level.
- **Smart-Watch** to be worn by the subject on the dominant hand. The smart-watch used in our experiment is Samsung Gear S2 Classic[2]. Data is collected via a custom *HRM Data Logger* background service app, that records raw accelerometer data sampled at 50Hz, and raw PPG data via a green LED sampled at 50Hz.

- **Android Mobile Device** with a companion app is used to control the data logging process during the experiment. The companion app communicates with the smart watch to start/stop the logging process as well as annotate the data as *STATIC* or *MOTION*.



(a) Real Crane Operator (b) Experimental Setup

Figure 6: Experimental Setup

- **Pulse Oximeter** (CMS 50D+ Finger pulse oximeter) is used as a ground truth device to record the heart rate of the subject during the data collection process. Raw PPG data (sampled at 60Hz) and HR (in BPM), from the pulse oximeter device is streamed and logged on a laptop (Ubuntu 14.04, 64-bit OS, connected via USB cable).

4.1.2 Data Collection Procedure

The subjects were asked to sit in a relaxed position, in front of the dummy crane lever, with the smart watch worn on their dominant hand. The index finger of the non-dominant hand is used to collect ground truth data (raw PPG and heart rate) from the pulse oximeter device, for the entire duration of the data collection process. Each data collection session was of 180 secs, subdivided into windows comprising 60 secs of rest, 40 secs of motion, 10 secs of rest, 40 secs of motion and 30 secs of rest. During the rest windows the subjects were instructed to relax and keep the dominant hand in a static position and the corresponding data collected is annotated as *STATIC*. During a given motion window the subjects were instructed to perform a sequence of hand movements to simulate the daily chores of a crane operator. This involves frequent steering of the crane lever and communicating with a walkie- talkie. The lever steering is simulated by a motion sequence as shown in Figure 7. Whereas walkie-talkie communication is simulated by picking up a mobile phone kept near to the lever, talk to it for few seconds and keep it back in place. If the subject completes the sequence of all the motion described, they are asked to repeat the sequence until the end of the window. The data collected during the motion windows are annotated as *MOTION*. Data collection process is controlled by an experimenter, who controls the mobile application, and also gives instruction to the subject (based on rest and motion windows) when to stay in rest position and when to perform motion in the respective windows based on a stopwatch. The motion sequence is explained to the subject a priori. Once the data collection is over the log files are extracted from the smart watch and then analyzed offline.

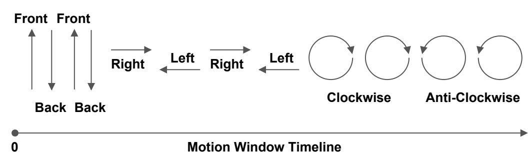


Figure 7: Crane Motion Simulation

4.2 Performance Measurement

Performance evaluation of the conducted experiments are done based on individual methods as stated below

- Performance of the Mobility Check algorithm with respect to the ground truth obtained by manual annotation.
- Random Forest classifier's performance analysis.
- Overall accuracy of HR Estimation.

It is worthwhile to mention that the complete algorithm is deployed in Samsung Gear S2 Classic device and the heart rates are estimated in real time. However performance evaluation is accomplished in offline mode in the interest of comfortability.

4.2.1 Performance Of Mobility Check Algorithm

The PPG and accelerometer database was collected for a total of 75 minutes (25 subjects 3 minutes each) We have analyzed the performance of Mobility Check Algorithm against the manual annotation of the window as "MOTION" or "STATIC". Total 1290 windows were gathered and 80:20 split has been chosen for training and testing. The Mobility Check Algorithm yields 92.24% accuracy in detecting motion windows and the confusion matrix is presented in Table 1.

[1]The clearance on ethical issues for handling and analysis of the data collected has been acquired from relevant body in Tata Consultancy Services Ltd. (TCS). Informed consent is also taken from the participants and the data is anonymized.
[2]http://www.samsung.com/uk/wearables/gear-s2/specs/

Table 1: Confusion Matrix for Mobility Check

MOTION	STATIC
96	12
8	142

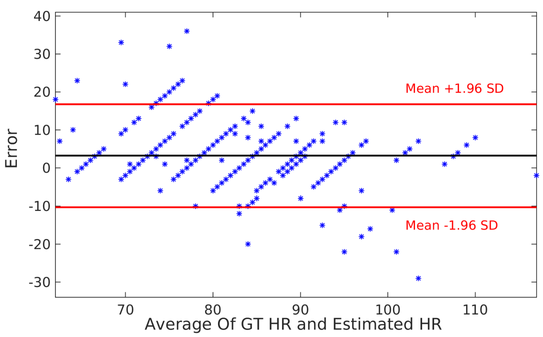


Figure 8: Bland-Altman plot of the HR estimation results for 25 Subjects

4.2.2 *Performance Of Random Forest Algorithm*

Random Forest Algorithm is responsible for ascertaining the right cardiac peak among the two highest peaks in PPG spectrum. This entails the further assessment of HR estimation accuracy. Based on the extensive analysis of PPG and Accelerometer spectrum, the right peak is outlined and categorized. The Random Forest Algorithm caters an accuracy of 88.88% in selecting the right peak of HR with a confusion matrix as shown in Table 2.

Table 2: Confusion Matrix for Random Forest

First Peak as HR	Second Peak as HR
36	6
6	60

4.2.3 *Overall accuracy of HR Estimation*

The Overall system performance is evaluated by estimating the HR error compared with the Ground Truth Heart rate. The Ground Truth Heart rate is calculated from the raw PPG signal obtained from the Pulse Oximeter device. For every time window, estimated HR and Ground Truth HR is analyzed. The Bland-Altman plot for all windows is outlined in Figure 8. The Limit Of Agreement(LOA) is [16.7615 -10.2920]. The LOA is defined as [μ + 1.96α μ - 1.96α] where μ is average difference and α is standard deviation. The mean and standard deviation for the absolute error is reported as 5.2 beats per minute (BPM) and 5.5 BPM respectively. Due to the limited time window (10 Sec), the FFT resolution is 0.1 Hz which signifies 6 BPM heart rate resolution error. Considering this resolution error, the above mentioned LOA is quite acceptable. Moreover, this evaluation is performed on real time heart rate measurement without employing any tracking algorithm. In the context of longitudinal analysis, we have further evaluated the performance of the system after post processing. Post processing caters heart rate for every minute. Table 3 reports the mean absolute error (MAE) and standard deviation (STD) respectively.

Table 3: Post Processing Result

MAE	3.2
STD	4.65

5. CONCLUSIONS

In this paper, a wrist type PPG based HR monitoring algorithm is presented to monitor the wellness of the crane operator. In the motion, the algorithm leverages the accelerometer signal and exploits the Random Forest Classifier to identify the PPG peak associated with cardiac rhythm. While in static phase, more conventional frequency based analysis is opted to estimate the HR. This dual approach based on mobility abates the computational complexity and increases the efficacy of the system. It is noteworthy to mention that the algorithm is deployed on a wearable platform which offers the high degree of usability in terms of practical deployment to the field. Experimental results obtained from the 25 datasets achieves the average absolute estimation error of 5.2 BPM with the standard deviation of 5.5 BPM which further supports the effectiveness of the system.

6. ADDITIONAL AUTHORS

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