Estimation of ECG Parameters using Photoplethysmography

Rohan Banerjee, Aniruddha Sinha, Arpan Pal and Anurag Kumar

Abstract— **Regular ECG check up is a good practice for cardiac patients as well as elderly people. In this paper we propose a low cost methodology to coarsely estimate the range of some important parameters of ECG using Photoplethysmography (PPG). PPG is easy to measure (even with a smart phone) and strongly related to human cardio-vascular system. The proposed methodology extracts a set of time domain features from PPG signal. A statistical analysis is performed to select the most relevant set of PPG features for the ECG parameters. Training model for the ECG parameters are created based on those selected features. Both artificial neural network and support vector machine based supervised learning approach is used for performance comparison. Experimental results, performed on benchmark dataset shows that good accuracy in the estimation of ECG parameters can be achieved in our proposed methodology. Results also show that the overall performance improves in using feature selection technique rather than using all the PPG features for classification.**

I. INTRODUCTION

Electrocardiogram (ECG) is a way to measure the electrical activity of heart. ECG signal is generated due to periodic depolarization and repolarization of atria and ventricle in heart [1]. ECG is the most popular and clinically proven method for checking heart condition of a person. Regular ECG monitoring is a good practice for patients suffering from heart deceases as well as elderly people who are prone to heart attack. But, it might not be feasible for all to have a day to day clinical ECG diagnosis. Driven by the the fact, we propose a low cost, simple way to estimate some basic ECG parameters of a person using Photoplethysmography. Rather than proposing a new diagnostic tool, our goal is to provide a low profile initial screening system, that is capable of generating alert for possible unwellness and refer to a detail medical check up.

Photoplethysmography (PPG) is a simple, inexpensive and non-invasive method to measure the instantaneous change in blood volume in blood vessels in an optoelectronic way [2]. PPG can be easily measured by illuminating the tissues with a light source (LED) that allows light to pass through the blood vessels, and a photo detector, placed at the other end, to detect the reflected light [6]. PPG signal is periodic in nature and is synchronized with the cardiac cycle [3] [4]. In recent years, PPG has been extensively drawing the attention of medical researchers and scientists for direct and indirect estimation and measurements of different physiological parameters [5]. PPG is widely used for the measurement of the variability in heart rate [4] and SpO2 (Saturation of peripheral oxygen) in doctor clinics and diagnostic centers [6]. Moreover there have been simple, inexpensive devices commercially available for recording PPG signals from peripheral body parts like fingertip, ear lobe [6]. Recently, there has been a trend to capture fingertip PPG signal using high end smart phones having flash enabled camera. Grimaldi et al [7] proposed a method to measure fingertip PPG signal using smart-phone's camera and built-in LED. Gregoski et al. [8] also proposed a similar technique for android smartphone based PPG capturing technique. All these have made PPG based physiological sensing more appreciable and easily available, even in household.

Both ECG and PPG signals are directly synchronized with the human cardiac cycle [9]. The peak to peak interval of PPG signal is used to measures the heart rate which is highly correlated with the RR interval of ECG signal. Here in this paper, we have tried to coarsely estimate few important ECG parameters like PR interval, QRS interval, QT interval along with the RR interval from PPG. Ten dimensional time domain feature extraction is performed on each cycle of the recorded PPG signal. For feature extraction, we have used mainly the features presented in [10] with few additional features. The main features of ECG signals (PR, QRS, QT and RR intervals) are also extracted. There are quite a few existing solutions available to extract ECG features accurately. Mazomenos et al. in [11] proposed a time domain gradient based algorithm for ECG feature extraction. Zhao et al. [12] proposed a feature extraction method using wavelet transform and support vector machines. Here, wavelet transform coefficients are used as features for each ECG segment and SVM is used for classification. Castro et al. [13] and Mahmoodabadi et al. [14] also presented novel wavelet transform based approach for efficient ECG feature extraction. Tayel and Bouridy [15] used wavelet decomposition of the ECG images intensity to obtain ECG features that are processed using artificial neural networks. Chouhan and Mehta [16] presented an algorithm, that employs a modified definition of slope of ECG as the feature to detect QRS complex. Saxena et al. [17] developed a combined wavelet transforms technique for ECG analysis. They used a quadratic spline wavelet (QSWT) for QRS complex detection and the Daubechies six coefficient (DU6) wavelet for P and T points detection.

The extracted ECG parameters (features) are divided into different levels (like High, Medium or Low), based on their ranges for simplicity of the solution and also to improve the overall detection accuracy. An offline feature selection is performed on the extracted PPG feature set to select those

Rohan Banerjee, Aniruddha Sinha and Arpan Pal are with Innovation Lab, Tata Consultancy Services Ltd., India {rohan.banerjee, aniruddha.s, arpan.pal}@tcs.com

Anurag Kumar is a student of Indian Institute of Technology, Delhi ranurag92@gmail.com

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features that are strongly related to the ECG parameters. Training model for different ECG parameters are created using the selected PPG features. The main contribution of the paper is

- Estimation of the range of ECG parameters from PPG signal.
- Efficient selection of PPG features based on maximal information coefficient (MIC).
- Supervised learning mechanism for classification.

Rest of the paper is organized as follows. Section II introduces the solution approach for the problem definition. Section III describes the detail methodology of our proposed solution. Section IV details the experimental results, followed by conclusion in section V.

II. Problem Definition and Solution Approach

Each cycle of ECG signal consists of three important segments (as in Fig. 1), namely the P wave, the QRS complex and the T wave. The P wave is caused due to depolarization of atria, QRS complex corresponds to the depolarization of ventricle and T wave corresponds to the repolarization of ventricle. Thus the PR interval is a good measurement for checking the condition of atria and QT interval reveals the condition of ventricle [18]. Whereas, RR interval is used to measure the heart rate. A prolonged PR interval indicates a possibility of first stage heart block. A prolonged QT interval is a risk factor for ventricular tachyarrhythmias. A less RR interval indicates high value of heart rate and vice versa. Thus, a good estimation of the range of the ECG parameters (rather than actual value) can coarsely predict the heart condition of a person (for initial screening purpose). Here, in this paper, we propose to estimate four important ECG parameters, PR, RR, QRS and QT interval from PPG. For experimental purpose, we have used standard dataset containing simultaneously recorded ECG and PPG signal from several patients. An N dimensional feature set F is extracted from the PPG signal. An offline feature analysis is performed on the extracted feature set to select an M dimensional feature set G ($G \subseteq F$ and $M \leq N$) that is strongly related to a particular ECG parameter. The feature selection is performed based on maximal information coefficient (MIC) [20] and Pearson coefficient [24] as mentioned in section III-D. Feature extraction is done on ECG signals to extract the PR, QRS, QT and RR intervals. The ECG intervals are labeled into three to five levels (as in Table I). This leveling is done based on standard medical terminologies [18] [19]. The selected PPG features are used to create classifiers for the ECG parameters based on their predefined ranges. Artificial Neural Network (ANN) as well as Support Vector Machine (SVM) are used for performance analysis in classification. It is required to mention that the ECG feature extraction and offline selection of PPG features are performed in training phase only. In testing phase the selected features are extracted from PPG signal for estimation of ECG parameters.

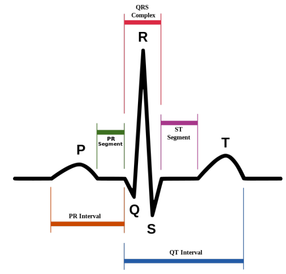


Fig. 1. A complete cycle of ECG signal (source:Wikipedia)

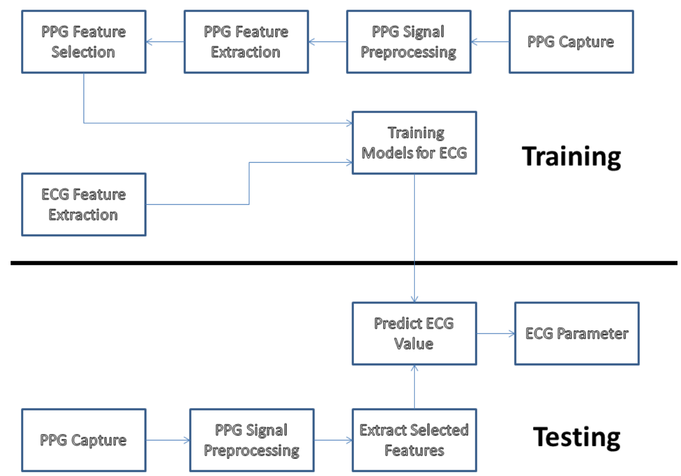


Fig. 2. Proposed ECG monitoring approach

III. Proposed Methodology

The block diagram of our proposed ECG monitoring system is shown in Fig. 2. The architecture contains two phases, training phase (model generation for ECG parameters) and testing phase (estimation of ECG parameters of an untrained subject from the training models). The main modules of our proposed architecture are explained below.

A. Preprocessing of PPG signal

PPG signal is extremely dependent to the properties of the subjects' skin structure, skin temperatures, ambient light, motion artifacts etc. So, proper care should be taken before PPG signal feature extraction. PPG signal generally contains a large but slowly varying DC part along with the AC component. Moreover, PPG signals are largely non stationary. So, a frame processing approach is taken to extract the stationary part out of it. PPG signal is segmented into fixed length small non-overlapping windows (5-10 second). Samples corresponding to each window are passed through a 4^{th} order bandpass Butterworth filter (cut-off frequency 0.25 Hz and 20 Hz) to remove the DC and high frequency noise components. The samples are further passed through a moving average filter for smoothing and to remove high frequency noise. Thus the PPG samples are prepared to feature extraction.

TABLE I

RANGE OF ECG PARAMETERS FOR CLASSIFICATION (MS-MILLISECOND, S-SECOND)

	Very low	Low	Normal	High	Very high
PR	NA	<120 ms	120-200 ms	>200 ms	NA
QRS	NA	<60 ms	60-100 ms	>100 ms	NA
QT	NA	<350 ms	350-470 ms	>470 ms	NA
RR	<0.6 s	0.6-0.8 s	0.8-1 s	1-1.2 s	>1.2 s

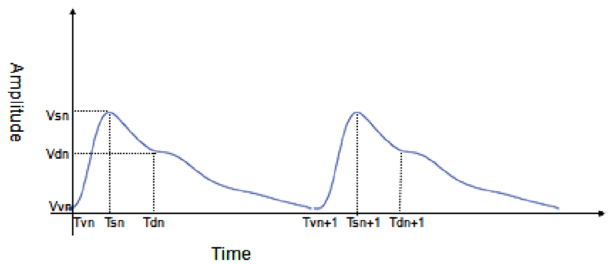


Fig. 3. PPG feature extraction

B. Feature Extraction of PPG signal

Fig. 3 shows a sample PPG waveform. Each cycle of PPG signal contains three important points, namely the peak (T_{s_n}, V_{s_n}), the valley (T_{v_n}, V_{v_n}) and the dicrotic notch (T_{d_n}, V_{d_n}). Ten dimensional time domain features are extracted from each PPG cycle based on these three points. The features ($F = \{f^1, f^2, f^3 ... f^{10}\}$ and $F \in R^{10}$), used by us in this paper are explained in (1) to (10).

$$\text{Peak to Peak Interval } (T_{pp}) = T_{s_n+1} - T_{s_n} \tag{1}$$

$$\text{Pulse Interval } (T_{pi}) = T_{v_n+1} - T_{v_n} \tag{2}$$

$$\text{Pulse Height } (V_{ph}) = V_{s_n} - V_{v_n} \tag{3}$$

$$\text{Crest Time } (T_{cr}) = T_{s_n} - T_{v_n} \tag{4}$$

$$\text{Delta Time } (T_{del}) = T_{d_n} - T_{s_n} \tag{5}$$

$$\text{Dict. time } (T_{dic}) = T_{d_n} - T_{v_n} \tag{6}$$

$$\text{Falling Time } (T_f) = T_{v_n+1} - T_{s_n} \tag{7}$$

$$\text{Dic2Min Time } (T_{dm}) = T_{v_n+1} - T_{d_n} \tag{8}$$

$$\text{Rising Slope } (S_r) = \frac{V_{s_n} - V_{v_n}}{T_{s_n} - T_{v_n}} \tag{9}$$

$$\text{Falling Slope } (S_f) = \frac{V_{v_n+1} - V_{s_n}}{T_{v_n+1} - T_{s_n}} \tag{10}$$

Out of the 10 features mentioned above, the first 5 features were proposed in [10]. These are incorporated with the rest, proposed by us. The feature extraction technique requires an accurate detection of the Systolic peak, valley and the dicrotic notch points from the PPG signal. A normal peak detection algorithm, capable of searching the local maxima and minima points from a function can compute the systolic peak and the valley points. Dicrotic notch is calculated by searching for the first local maxima in the first derivative of the the PPG signal between systolic peak and its immediate next valley point. In practice, PPG signals can be very noisy in nature due to various artifacts [2]. So there may be cases where some of these points are either wrongly detected or not detected at all, for some cycles, producing wrong values of the feature. So, an outlier removal mechanism is needed to perform on the extracted features to get rid of these potentially wrong features (noise).

C. Removal of Outlier

Generally the values of the wrongly detected features are either too large or too small than the normal range of the feature value. A histogram of k bins is computed for each of the extracted feature. The mid value of the range of i^{th} bin for j^{th} feature (f^j) is represented by (11).

$$B_i^j \text{ where } 1 \leq i \leq k \text{ and } 1 \leq j \leq 10 \tag{11}$$

Similarly B_{max}^j represents the mid value of the bin having maximum data entries for j^{th} feature. Since, the values of any PPG feature closely follow a Gaussian distribution, all the entries for m^{th} feature falling in t^{th} bin are passed for the next stage if the bin fulfills the following criteria in (12)

$$|B_{max}^m - B_t^m| \leq \mu \pm \sigma \text{ where } 1 \leq i \leq k \text{ and } 1 \leq j \leq 10 \tag{12}$$

Where μ and σ are the mean and standard deviation of that feature respectively.

D. Feature Selection

The success criteria of any machine learning based solution depends on efficient feature selection of the training set. Training with an improper set of features, can introduce high bias and/or high variance in the created classifiers. Here we have used the concept of maximal information coefficient (MIC) [20] and Pearson product-moment correlation coefficient (PPMCC) [24] for finding relationship between ECG parameters and our PPG feature set. MIC is a powerful parameter to measure any kind of linear or non-linear associations existing between a pair of variables. MIC does so by constructing grids with various sizes to find the largest mutual information between a pair of data. The dependency between the pair of dataset is returned as a number between 0 and 1.

For a pair of dataset x and y, if I denotes the mutual information for a grid G, then MIC of a set D of data-pair with a sample size n and grid size less than $B(n)$ is given by [22] (13).

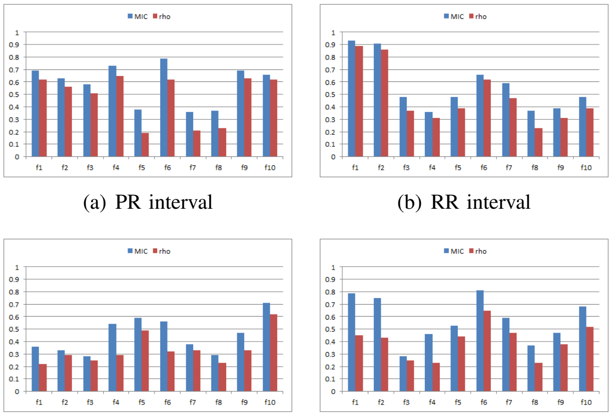
$$MIC(D) = max_{xy<B(n)}\{M(D)_{x,y}\} \tag{13}$$

where $B(n)$ is a function of sample size (usually $B(n) = n^{0.6}$). $M(D)$ is given by

$$M(D)_{x,y} = \frac{I^*.(D,x,y)}{\log min(x,y)} \tag{14}$$

and $I^*(D,x,y) = max\{I(D|G)\}$ for different distributions of G.

PPMCC in the other hand is used to find the linear relationship between a pair of dataset. For a pair of dataset x and y PPMCC (p) is the ratio of the co-variance of two



(a) PR interval (b) RR interval

(c) QRS interval (d) QT

Fig. 4. MIC and ρ value obtained from MIN.

variables to the product of their standard deviations and is given by [24] (15).

$$p = \frac{cov(x,y)}{\sigma_x.\sigma_y} = \frac{E[(x-\mu_x)(y-\mu_y)]}{\sigma_x.\sigma_y} \tag{15}$$

The range of p lies between -1 to +1. MINE [23] is a package to find relationship between large pair of dataset. Apart from MIC and PPMCC, MINE incorporates three more statistical features like maximum asymmetry score (MAS), maximum edge value (MEV), and minimum cell number (MCN) for finding relationship between a pair of data. Thus, we have used MINE tool to estimate relationship among different ECG and PPG features in our paper. However, we have mainly concentrated on two parameters - MIC and ρ $(1-(MIC-PMMC^2))$ in our case. Table II shows the relationship between an ECG feature x and PPG feature y, that can be derived from their respective MIC and ρ value.

MINE analysis for all the 10 PPG features with respect to PR, RR, QT and QRS interval are shown in Fig. 4. Here, the horizontal axis represents the index of the PPG features and the vertical axis represents the corresponding MIC and ρ value. From the MINE analysis we redefine our PPG features for PR (F_{PR}), RR (F_{RR}), QRS (F_{QRS}) and QT (F_{QT}) interval as follows:

$$F_{PR} = \{f^1, f^2, f^3, f^4, f^6, f^9, f^{10}\}$$
$$F_{RR} = \{f^1, f^2, f^6, f^7\}$$
$$F_{QRS} = \{f^4, f^5, f^6, f^{10}\}$$
$$f_{QT} = \{f^1, f^2, f^5, f^6, f^7, f^{10}\}$$

For a particular ECG parameter, we have included those PPG features in its redefined feature set, where the corresponding MIC value is higher than 0.5.

E. Classification

In training phase the selected PPG features are used to train different classifiers for ECG parameters. In testing phase the selected PPG features are used for prediction of the ECG parameters. We have used two supervised learning mechanism for comparing the performance of our PPG

TABLE II
DATAPAIR DEPENDENCY FORM MIC AND ρ VALUES

MIC	ρ	Datapair relationship
High	High	Strong and linear
High	Low	Strong but nonlinear
Low	Low	weak
Low	High	NA

feature set in ECG prediction: 1) Multiclass Artificial neural Network (ANN) and 2) Multiclass Support Vector Machine (SVM). Both ANN and SVM are very powerful and popular approach in machine learning. ANN [25] mainly follows a multi-layer Perception Model (MLP). SVM [26] in the other hand is a learning mechanism, based on the principle of structural risk minimization [27] from learning theory. It is hard to prefer a particular classifier out of these two, as there performance varies from problem to problem.

IV. Experimental Results

We have used the Capnobase TBME RR dataset [21] for testing the performance of our proposed methodology. This is an annotated dataset [29], containing ECG and PPG samples for 42 patients with 8 minute of data for each, at a sample rate of 300. Due to heavy noisy data, we rejected 4 files and continued processing with 38 files. The dataset was split into two parts, one part for training and the rest for testing. The performance analysis was done in two stages.

- Firstly, the overall performance was tested with the 10 dimensional PPG features, bypassing the feature selection phase.
- Secondly, selected features as mentioned in section III-D were used for performance analysis.

Both ANN and SVM were used for performance comparison in both the cases. For ANN we used a single hidden layer with 7 nodes. It was observed that, the performance did not have a significant effect in increasing the number of hidden layers and number of nodes per hidden layer. For SVM we used Radial basis function (RBF) [28] as the kernel. Table III shows the overall detection accuracy using all the PPG features. Table IV in the other hand, shows the system performance with selected PPG features. In both the cases, the class decision is made based on maximum occurrence in an aggregated data of 30 seconds to ignore the instantaneous fluctuation of some of the ECG parameters. The accuracy mentioned here is also the average accuracy obtained by combining all the test subjects. The following observations can be made from the experimental results

- The SVM classifiers perform better than their ANN counterparts in most of the cases.
- The overall accuracy for QT, RR and PR interval improves using the reduced feature set over the entire feature set.
- The QRS parameter does not show any positive effect in PPG feature selection. One possible reason for this may be QRS does not hold a very strong relationship

TABLE III

PERFORMANCE ANALYSIS ON USING ALL THE PPG FEATURES

ECG param	With ANN (%)	With SVM (%)
PR	83.1	87.5
RR	90.3	91.6
QRS	84.7	86.3
QT	87.6	88.3

TABLE IV

PERFORMANCE ANALYSIS ON USING SELECTED PPG FEATURES

ECG param	With ANN (%)	With SVM (%)
PR	88.5	90.3
RR	93.9	94.6
QRS	84.1	84.9
QT	91.1	92.6

with any of the 10 feature (as indicated in low values in Fig. 4(c)). Thus, feature selection does not boost up its overall accuracy. A new set of features may improve its detection accuracy.

We found from performance analysis in individual subject level that, sometimes the accuracy reduces (80% or less) for those subjects where the ECG parameters are rapidly fluctuating and distributed in more than one bins in a small time interval. Subjects having less fluctuating ECG, shows much improved accuracy (90% or higher).

V. CONCLUSION

This paper introduces a methodology for coarsely estimating some of the ECG parameters from PPG. Here, we have worked on standard medical dataset for research. Experimental results show that, the feature selection technique improves the coverall system performance than using the entire feature set. Results also reveal that our present system produces the best accuracy in estimating RR interval. Whereas, an improved relationship of the QRS interval with different PPG features still needs to be explored. In future, we plan to develop a mobile phone application that can estimate the ECG parameters by capturing PPG from a person. The present work can be further improved by proposing new PPG features (both time and frequency domain) along with investigating the system performance with other standard feature selection algorithms. In future we plan to enhance the work with adding more PPG features along with the external features like height, weight, age of the subject on an enhanced and more diverse dataset for more accurate and generic ECG monitoring.

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