PHOTOECG: PHOTOPLETHYSMOGRAPHY TO ESTIMATE ECG PARAMETERS

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ABSTRACT

This paper presents a simple method to indirectly estimate the range of certain important electrocardiogram (ECG) parameters using photoplethysmography (PPG). The proposed method, termed as PhotoECG, extracts a set of time and frequency domain features from fingertip PPG signal. A feature selection algorithm utilizing the concept of Maximal Information Coefficient (MIC) is presented to rank the PPG features according to their relevance to create training models for different ECG parameters. The proposed method yields above 90% accuracy in estimating ECG parameters on a benchmark hospital dataset having clean PPG signal. The same method results an average of 80% accuracy on noisy PPG signal captured by iPhone, indicating its feasibility to create phone applications for preventive ECG monitoring at home.

***Index Terms*—** photoplethysmography, electrocardiogram, feature selection, classification

1. INTRODUCTION

Electrocardiogram (ECG) is a popular medical diagnosis to check the heart condition of a person. It is widely recommended as a preliminary test to be carried out by patients, feeling any kind of chest problem. An alarming study of World Health Organization (WHO) [1] reveals that more than 23 million people will succumb annually from cardiovascular diseases by 2030. Due to urban lifestyle and stresses at work place, daily health tips are often neglected. As a result, young people, even aged under 35 are now prone to sudden cardiac arrests [2]. Thus, simple, low cost and portable solutions to regularly monitor vital physiological parameters like heart-rate, blood pressure and ECG at home are drawing attention as part of preventive healthcare.

Photoplethysmography (PPG) is a simple and inexpensive way to measure the instantaneous change of blood volume in blood vessels [3]. Cheap commercial devices are available to capture PPG signal from human peripheral body parts like fingertip for measuring heart rate. Moreover, in today's ubiquitous world, there are applications that capture reflective PPG signal using a mobile phone having high quality camera with flash. Grimaldi et al. [4] and Gregoski et al. [5] proposed such techniques using android smart phones. Pal et al. developed an iPhone application [6], that captures reflective PPG signal and removes the noisy part out of it, using RGB analysis for robust heart rate measurement.

A complete ECG cycle contains five major points (P, Q, R, S and T) and few time interval parameters (PR, QRS, QT) for checking heart condition. A prolonged PR interval indicates a possibility of first stage heart block [7]. A prolonged QT interval, caused due to effects of certain drugs is a risk factor of ventricular tachyarrhythmias [7]. RR interval indicates the heart rate. Thus, rather than measuring accurate values, an estimation of the range of PR, QRS or QT interval can indicate the heart condition of a person for initial screening purpose and alert generation at home.

Both ECG and PPG are directly synchronized with human cardiac cycle. The peak to peak interval of PPG is known to be highly correlated with the RR interval [3], indicating the possibility of deriving other ECG parameters from PPG. In this paper we propose an approach to predict the range of PR, QRS and QT intervals along with actual value of RR interval parameter of a person from PPG. Although the method does not claim to compete with the accurate ECG machines, it introduces a simple initial screening system (possibly a phone application) for household ECG monitoring. The main contribution of the paper are:

- Machine learning based approach to estimate the range of ECG parameters using PPG features.
- A novel feature selection approach using sigmoid gain function based on Maximal Information Coefficient (MIC), resulting in better accuracy.
- Removal of outlier feature data for improving the performance on noisy PPG data.

Our experimental dataset is explained in Section 2. The details of our methodology and results are given in Section 3 and 4 respectively, followed by conclusion.

2. EXPERIMENTAL DATASET

We have used two datasets for experimental purpose. Capnobase TBME-RR [8] [9] is a benchmark hospital dataset containing simultaneously recorded PPG and ECG data for 42 patients each with 8 minutes duration, sampled at 300 Hz.

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Table 1. Range of ECG Parameters for Classification.

	Low	Normal	High
PR	< 120 ms	$120 - 200$ ms	> 200 ms
QRS	< 60 ms	$60 - 100$ ms	> 100 ms
QT	< 350 ms	$350 - 470$ ms	> 470 ms

It covers all the ranges of PR, QRS and QT interval parameters as shown in Table 1, along with a wide variation of heart rate and hence is an ideal dataset for testing the performance of our proposed method.

We collected a second dataset for further performance analysis. Twenty five subjects, including male and female subjects, aged between 22-40 in uniform distribution participated in this process. The method proposed by Pal et al. [6] was implemented in an iPhone 4 for capturing reflective PPG at 30 Hz sample rate. ECG of an individual was simultaneously recorded using Etcomm Bluetooth ECG [10] device. This dataset also covers all the ranges of ECG parameters, but is noisier than Capnobase. The performance of our method is evaluated on this dataset to test its viability to create phone applications for ECG parameter estimation.

3. METHODOLOGY

Our methodology consists of two phases, training and testing. Training models for PR, QRS, QT and RR intervals are created in the off-line training phase. A set of M features ($F_{tot} \in \mathbf{R}^M$), including T time domain features ($F_t \in \mathbf{R}^T$) and F frequency domain features ($F_f \in \mathbf{R}^F$) are extracted from the PPG signal. Here $F_{tot} = F_t \cup F_f$ and $M = T + F$. The subjects simultaneously undergo an ECG check-up for extracting ground truth PR, QRS, QT and RR intervals. There are numerous algorithms available in literature for ECG signal analysis. Wavelet transform based ECG parameter extraction methods were proposed in [11] [12] [13]. Several tools (like ECGBag [14]) are also available for locating the major points in ECG waveform. A time domain feature extraction from noisy ECG waveform was presented in [15]. A combination of all these methods were used by us for ECG analysis. Extracted PR, QRS and QT interval values are binned into one of the three classes as shown in Table 1, in terms standard medical definition [16]. A feature selection technique, influenced by the theory of MIC [17], followed by a sigmoid gain function is used to rank the PPG features according to their relevance with the ECG parameters for creating different training models. During testing, ECG parameters of an untrained subject are predicted by analyzing his/her PPG features, using the training models.

Different modules of our proposed methodology are elaborated in the following subsections.

3.1. PPG Signal Preprocessing

Spectrum of PPG signal is typically concentrated around 1 Hz. Thus, a 4^{th} order bandpass filter (cut-off frequencies 0.25 Hz and 7 Hz), and a moving average filter are used to remove the undesired frequencies from raw PPG signal.

3.2. PPG Feature Extraction

We start with 15 PPG features, including 11 time domain and 4 frequency domain features for analysis.

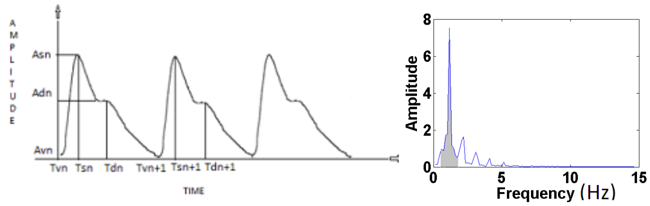

Fig. 1. (a) Sample PPG signal with 3 full cycles and its (b) frequency components.

3.2.1. Time Domain Features

The time domain features are extracted from each cycle of PPG signal. It can be observed in Fig. 1.(a) that a complete PPG cycle is bounded by two successive trough points. So all the troughs are located in the input PPG data to identify the cycles. Our 11 time domain features ($F_t = \{f_1, f_2, f_3, .., f_{11}\}$) are - (1) *peak to peak interval* ($T_{s_n+1} - T_{s_n}$), (2) *pulse interval* ($T_{v_n+1} - T_{v_n}$), (3) *pulse height* ($A_{s_n} - A_{v_n}$), (4) *crest time* ($T_{s_n} - T_{v_n}$), (5) *delta time* ($T_{d_n} - T_{s_n}$), (6) *trough to notch time* ($T_{d_n} - T_{v_n}$), (7) *falling time* ($T_{v_n+1} - T_{s_n}$), (8) *notch to trough time* ($T_{v_n+1} - T_{d_n}$), (9) *rising slope* ($(A_{s_n} - A_{v_n})/(T_{s_n} - T_{v_n})$), (10) *falling slope* ($(A_{v_n+1} - A_{s_n})/(T_{v_n+1} - T_{s_n})$) and (11) *area under a complete cycle*. Some of these features are taken from [18] and [19] with the rest proposed by us. Effective feature extraction requires an accurate detection of the peak (T_s, A_s), trough (T_v, A_v) and dicrotic notch (T_d, A_d) from every cycle. Once the peaks and troughs are detected, dictrotic notches can be traced by searching the local maxima in the first derivative between a peak and its immediate trough [18].

3.2.2. Frequency Domain Features

A Short Time Fourier Transform (STFT) is applied on the windowed PPG samples to obtain the frequency domain features. If $[x_n, x_{n+1}...x_{n+N-1}]$ be a discrete sequence of length N, then the expression of N point STFT for k^{th} bin corresponding to $f_k = k.f_s/N$ Hz (f_s being sampling frequency) of the windowed sequence $x[n + m].w[m]$ is given by

$$X(n, k) = \sum_{m=0}^{N-1} x[n + m]w[m]e^{-j(2\pi/N).k.m} \quad (1)$$

The major frequency components of a sample PPG signal is shown in Fig. 1.(b). Here the dominant peak indicates the fundamental component of the signal. The other peaks are possibly associated with different waves reflected from periphery to aorta [19]. For optimum performance, PPG samples are segmented into non-overlapping rectangular windows of 1024 and 256 samples for Capnobase and phone dataset respectively. Four frequency domain features ($F_f = \{f_{12}, f_{13}, f_{14}, f_{15}\}$), such as 1) *dominant peak location*, 2) *distance between dominant and its immediate peak*, 3) *spectral centroid* and 4) *width of dominant peak region* (shaded region in Fig. 1.(b)) are extracted from each window.

3.2.3. *Constructing the Complete Feature Set*

Time domain features are extracted from each of the PPG cycles, but frequency domain features are extracted from every window. A complete window contains m full cycles along with one or two partial cycles at the beginning and or at the end. The frequency domain features extracted from that window are repeatedly assigned to the time domain features corresponding to all m full cycles for constructing the composite time frequency feature space. The cycles partially in between two successive windows are assigned with the average values of the frequency domain features of the two. So, for each subject M_o feature vectors are generated in $\mathbf{R}^{15}$ space, where M_o is the number of complete cycles in the captured data.

3.3. Removal of Outlier

PPG signal is noisy in nature and may contain intermediate false peak or trough points. Moreover sometimes actual peaks or trough points are completely missed out due to noisy surroundings. These result in the calculation of wrong features (outlier) in the feature extraction stage.

The proposed approach creates two clusters [20] to successfully remove the wrong features. If i^{th} instance of j^{th} feature be f_j^i, then for all i, we calculate

$$\Delta f_j^i = |f_j^{i+1} - f_j^i|, 1 \leq j \leq 15 \tag{2}$$

Since for a subject, values of j^{th} feature in two successive cycles or windows should not vary much, Δf_j^i should be very close to zero. A high value of Δf_j^i indicates that either of f_j^i or f_j^{i+1} is wrongly calculated.

Initially, histogram analysis is done for all the Δf_j^i to initialize the centroids for the cluster analysis. Later a 2-Means clustering is done followed by cluster density estimation to remove the outliers. In the histogram analysis, for the j^{th} feature, if bin k_j holds the maximum data points from Δf_j, then the average value of all the entries in k_j represents the j^{th} component of the initial centroid ($C1_j$) for one cluster. The initial centroid of the second cluster ($C2$) is the farthest data point from the $C1$. A standard k-Means algorithm is applied to get the final cluster centroids. The features corresponding to the centroid with lower Xie-Beni index [21] are considered to be compact and consisting of good data points. These are used for further processing.

3.4. Feature Selection

Feature selection aims to select the most relevant set of features for training a classifier. It is often seen that, training with a reduced but discriminative set of features can improve the accuracy of a learning system. In this paper we propose an effective feature selection method using the concept of MIC. MIC is a statistical tool to measure the relationship existing between a pair of dataset [17]. This is done by constructing grids with various sizes to find the largest mutual information between the data pair. A high value of MIC (~ 1) indicates a stronger interrelationship. For each pair of data (x, y), if I is the mutual information for a grid G, then MIC of a set D of pairwise data with sample size n and grid size (xy) less than $B(n)$ is given by (3) [22]

$$MIC(D) = max_{xy<B(n)}\{M(D)_{x,y}\} \tag{3}$$

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

$$M(D)_{x,y} = \frac{max\{I(D|G)\}}{\log min(x,y)} \tag{4}$$

Fig. 2 shows the MIC values obtained for all the 15 PPG features corresponding to different ECG parameter classes for training dataset. If the MIC of n^{th} PPG feature f_n with respect to an ECG parameter be w_n, then we calculate a gain factor G_n from it using a sigmoid function as in (5)

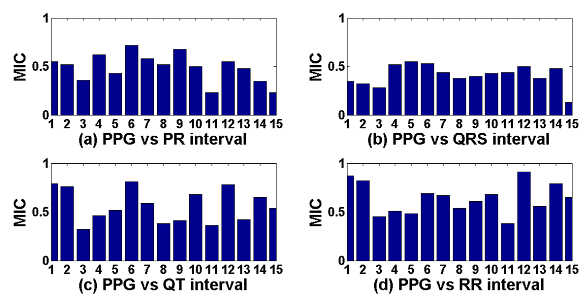

Fig. 2. MIC of 15 PPG features w.r.t. ECG parameters.

$$G_n = \frac{1}{1 + e^{-k \cdot (w_n - 0.5)}} \tag{5}$$

The features are multiplied by their respective gain factors before training or classification. The constant k controls the steepness of the gain function (as in Fig. 3(a)). The function forms a horizontal line at $k = 0$, resulting equal gain of 0.5 for all values of MIC. This is equivalent to a no feature selection criteria. The steepness gradually increase with k. So, features, holding high MIC values (≥ 0.5) are boosted with gain factor close to 1. However, features with lesser MIC values are gradually suppressed due to their close to zero gain. Thus an effective feature selection is possible by optimally tuning the constant k. In systems perspective, calculation of gain factors from MIC for different PPG features is done in training phase and are used for both training and testing. The proposed feature selection method is tested on Iris dataset. It contains a total of 150 instances of 3 different classes of Iris flower, defined by 4 dimensional feature space (sepal length, sepal width, petal length and petal width). MIC values of the 4 features with the class level are obtained as

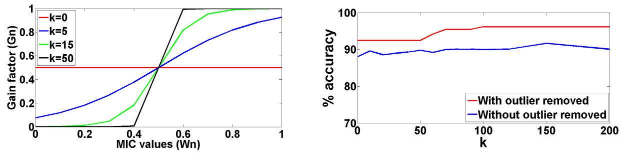

Fig. 3. (a) Plot of sigmoid gain function for different values of k. (b) Effects of outlier removal on QT interval.

$\{0.64, 0.4, 0.92, 0.92\}$, indicating that third and fourth features are more significant. The same is reported by other standard feature selection algorithms [23] [24], justifying our proposed MIC based approach.

3.5. Classification

Certain PPG features $\{f_1, f_2, f_6, f_{12}, f_{14}, f_{15}\}$ are found to hold good linear relationship with RR interval by producing high Pearson coefficient (above 0.8 in magnitude) values. So, linear regression produces satisfactory results in estimating actual value of RR interval. However this does not hold for PR, QRS and QT interval parameters. Hence, instead of predicting actual values, we use a multiclass Support Vector Machine (SVM) classifier, with C-SVC [25] algorithm and radial basis kernel to predict their ranges as in Table 1.

4. EXPERIMENTAL RESULTS

Our proposed method is tested on benchmark Capnobase dataset and the second dataset collected by us using iPhone. Both were split into two parts in 60:40 ratio, the larger part for training purpose and the smaller for performance analysis. All the ranges of PR, QRS and QT intervals are ensured to represent equally in the training dataset. Like feature extraction, classification is also done on individual cycle of PPG signal. The average detection accuracy (in percentage) is considered as the evaluation criteria for PR, QRS and QT interval classes. Whereas, average percentage error from ground truth value is reported for RR interval. The effect of outlier removal on QT interval, using Capnobase dataset by varying the steepness constant k is shown in Fig. 3(b). It shows that the detection accuracy improves with outlier removal for all values of k. Similar performance is achieved for other ECG parameters as well. Thus, we report all our results by incorporating the same. Overall performance in estimating different ECG parameters using the two datasets, for different values of k are shown in Fig. 4. It can be observed that for all the ECG parameters, overall accuracy mostly improves with k and generally is the least at $k = 0$ (equal gain to all features i.e no feature selection). This clearly indicates the positive effect of feature selection. It is also observed that, for a particular ECG parameter, optimum performance for both datasets is achieved around same value of k, justifying that the feature selection method is dataset independent. The proposed methodology inevitably produces better accuracy on Capnobase dataset than the other. Since iPhone device

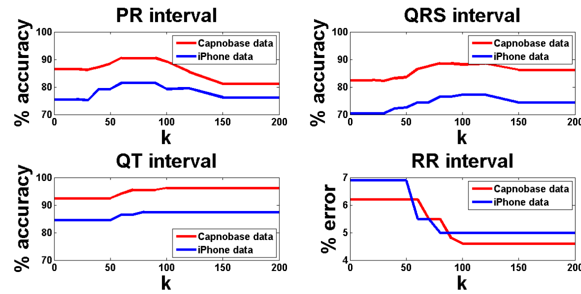

Fig. 4. Performance of ECG classifiers for different values of k for the two datasets.

captures reflective PPG at a lesser sampling rate, it is dependent on subject's skin properties, motion artifacts and surrounding light. Being a standard dataset, Capnobase PPG dataset is mostly free from them. In spite of the noisy data, we are able to achieve around 80% accuracy on our second dataset in estimating PR, QRS and QT interval parameters. This indicates the feasibility of the proposed method to create phone application for household ECG monitoring. It is also observed that, the performance of PR and QRS interval classifiers initially improves with k, but eventually degrades at a very high value of k. One possible reason may be, at a very high value of k, some discriminative features, but holding low MIC values (≤ 0.5) with ground truth, get eliminated, resulting in lower accuracy. However, this effect is not observed for QT and RR intervals. Holding stronger relationship with most of the PPG features, the QT interval classifiers performs better than PR and QRS intervals.

We found by analyzing every individual subject that, those having prominent dicrotic notch in PPG signal, produces better accuracy than others in detecting different ECG parameters. Since, many of our features are derived from dicrotic notch points, wrong estimation of them may lead to erroneous feature calculation and hence reduced accuracy. Currently, we are investigating the feasibility of using the curvature of a subject's PPG waveform as an alternative feature to bypass the depecdency of noise-prone dicrotic notch points.

5. CONCLUSION

The paper presents an empirical approach to estimate some ECG parameters from PPG. The method is successfully tested on two datasets to justify its suitability for coarse ECG estimation even on noisy PPG data for initial screening. The proposed feature selection algorithm boosts up the overall detection accuracy by selecting the relevant features for classification. Currently, we are at the very first stage of PhotoECG project. The method still needs to be tested on larger and more diverse dataset before actual system deployment. Our future work concentrates in proposing new PPG features relevant to ECG and also to integrate them with other easy-to-measure cardiovascular features to search for better accuracy.

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