Cardiac Arrhythmia Detection using Photoplethysmography

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Abstract— **Cardiovascular Diseases (CVDs) cause a very large number of casualties around the world every year and cardiac arrhythmias contribute to significant proportion of CVD related deaths. Bedside cardiac activity monitors in hospitals are based on electrocardiogram (ECG) processing and are known to produce too many false alarms. Moving beyond bedside care, ECG is not very suitable for use in wearable devices. Photoplethysmography (PPG) on the other hand provides an inexpensive and more wearable device-friendly alternative. This work presents a technique to detect life threatening arrhythmias using only PPG waveforms. PhysioNet Challenge 2015 data is used to detect five types of arrhythmias namely, tachycardia, bradycardia, asystole, ventricular tachycardia and ventricular fibrillation. A novel technique is employed to assign pulse quality index to every PPG pulse and highest quality portion of the signal is used for detection. Results indicate that PPG provides a viable alternative for conventional ECG based detection. An overall true positive rate (TPR) of 93% was achieved with true negative rate (TNR) of 53.78% suggesting that PPG is a viable option for arrhythmia detection.**

I. INTRODUCTION

CVDs are a leading cause of casualties around the world. According to World Health Organization report of 2012, nearly 31% of all global deaths were caused by CVD [1]. These numbers are on the rise in developing countries. Among the CVDs, cardiac arrhythmia is most common with millions of people suffering from it. An arrhythmia is a problem with the rate or rhythm of heartbeat where heart beats too quickly, too slowly, or with an irregular pattern. Arrhythmias are classified under code 427 in ICD-9 (International Classification of Diseases) and I47 to I49 in ICD-10 codes [2]. Arrhythmias are responsible for up to 80% of sudden cardiac arrest cases which leads to around 12% of all deaths in a year [3]. ECG based bedside cardiac monitoring systems are used in hospitals to report occurrence of arrhythmia. In most cases, these systems are responsible for producing far too many false alarms. False alarms as high as 86% have been reported and around 6% to 40% of such alarms are found to be true but clinically insignificant [4]. Also, a very small percentage of all alarms flagged by monitoring systems, about 2% to 9% are found to be significant [5].

PhysioNet launched a challenge in 2015 to develop new methods utilising PPG and arterial blood pressure (ABP) signals along with ECG to reduce false alarms [6]. ABP signals are invasive and are limited for hospital use. PPG on other hand uses light based sensors which makes it an excellent choice for wearable devices even better than ECG which requires electrodes. This property makes PPG most practical for home monitoring is the method of choice for this work. This work is aimed at utilizing only PPG signals to detect various life threatening alarms and not just suppress false alarms.

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II. DATASET

PhysioNet challenge dataset used for evaluation of this work, provides bedside monitor data leading up to a total of 1250 life-threatening arrhythmia alarms recorded from three of the largest intensive care monitor manufacturers' bedside units recorded in four hospitals in the USA and Europe, chosen at random. The data is split between training (750 alarms) and testing (500 alarms) of which only training set is made available and testing set is reserved for scoring. Half of training data consists of 5 minute long recordings, sampled at 250Hz. The annotated alarms in the data are triggered in the last 10 seconds of the recording, i.e. between 4:50 to 5:00. Remaining half consist of recordings which have 30 seconds additional data following time of the alarm making them 5:30 minutes long. Five types of arrhythmias are included in the data, tachycardia, bradycardia, asystole, ventricular tachycardia and ventricular fibrillation. Each recording contains 2 ECG channels and one or more pulsatile waveforms like PPG or ABP. In all, the data contains 628 PPG recordings which are used in this work.

III. PROPOSED METHOD

Arrhythmia detection is carried out using instantaneous heart rate estimated from the PPG signals and involves three major steps. The first step assigns a novel pulse quality index to individual pulses and the overall signal. This step is necessary as PPG signals are degraded due to noise and motion artifacts which can lead to incorrect pulse rate detection. This index is based on morphological features of each individual pulse as well as characteristics of the entire signal. Each pulse is expressed as a combination of two Gaussian curves. Along with the coefficients of the Gaussian curves, pulse height and number of local peaks are used as local morphological features towards calculating PQI. Global characteristic of signal is captured using a novel concept used in image processing termed as spectral residual representation. Appropriate threshold is set for each pulse based on its PQI and instantaneous heart rate is estimated. Artifact corrupted pulses are be removed using the quality index and use highest quality pulses are selected for estimating heart rate which forms the second step. In the last step, arrhythmia

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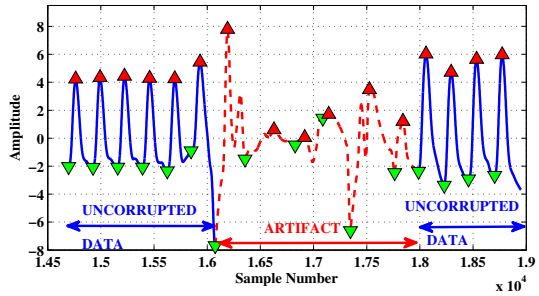
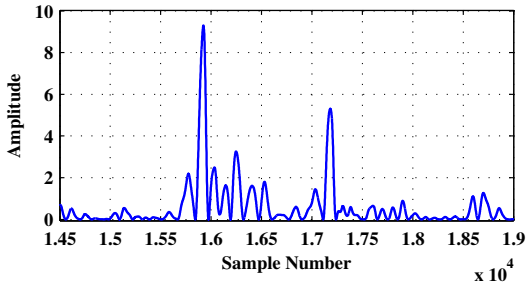


(a) PPG signal corrupted by motion artifact



(b) Spectral residual representation of the corrupted signal in Figure. 1a

Fig. 1: PPG with artifact and its residual representation

detection is carried out using the heart rate and definition for corresponding arrhythmia. Following sections discuss the process in detail.

IV. PQI ASSIGNMENT

A. Preprocessing and Pulse Segmentation

PPG signals are passed through a moving average filter of window 20 to remove noise. The filtered signal is divided into pulses based on local peaks and troughs.

B. Spectral Residual Representation

The concept of spectral residual of a signal is introduced in [7] and is primarily used for creating a saliency map of an image which is essentially a two-dimensional signal. The technique is slightly modified for application in case of a one-dimensional signal such as a PPG data. Residual representation highlights high frequency foreground objects of an image from the low frequency background. This idea is extended to an artifact corrupted data which can be considered as regular PPG pulses (low frequency content) mixed with artifact (high frequency content). As the residual highlights the high information content regions of an image, in case of PPG, the spectral residual shall highlight the areas of high signal variation which are essentially artifacts.

To obtain residual representation, given PPG data, $x(n)$, is first converted into frequency domain using Fourier Transform.

$$A(f) = Re[F\{x(n)\}],\ P(f) = Im[F\{x(n)\}] \qquad (1)$$

where F is the Fourier Transform. Re and Im denote the real and imaginary components of the Fourier Transform. $P(f)$ is the phase spectrum of the given signal and is unaltered. The magnitude, $A(f)$ is converted into logarithmic scale. The log spectrum is averaged using a moving average

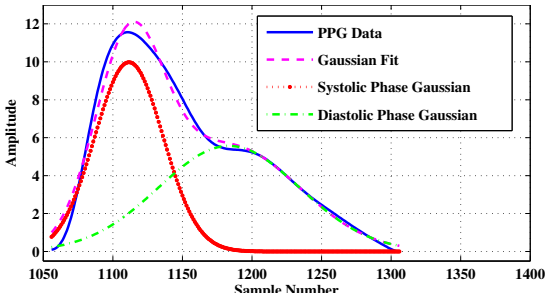


Fig. 2: Gaussian Fitting for PPG signal

filter, $H_m(f)$ with window size m. A modification is made in estimating the residual here. Instead of removing this averaged component of log spectrum from the original log spectrum, residual is estimated directly form the averaged log spectrum. This modification is necessary as the variation in PPG signal characteristics caused by artifacts is not as significant as the variation in pixel intensities caused by objects.

$$L(f) = log\{A(f)\},\ R(f) = H_m(f) \cdot L(f) \qquad (2)$$

$R(f)$ denotes the residual representation. Once the representation is obtained, it is converted back in time domain by Inverse Fourier Transform. The Gaussian filtering used in [7] at this stage is skipped.

$$r(n) = F^{-1}[exp\{R(f) + P(f)\}]^2 \qquad (3)$$

Here, F^{-1} denotes Inverse Fourier Transform. Typical residual of a PPG signal with artifacts is shown in Figure 1. The time domain residual is a discrete signal corresponding to every point of the input PPG data and represents global characteristic of the PPG. Feature selection and classification require a single value for a PPG pulse. Thus, the maximum value of residual over the length of a PPG pulse is assigned to the residual feature r_i for that particular pulse.

C. Gaussian Fit

The complete PPG cycle is composed of two significant phases, the systolic phase and the diastolic phase. The two phases can be distinguished from the placement of dicrotic notch. Using the knowledge of physiology of the PPG cycle, we express the PPG cycle as a combination of two Gaussian functions representing the two phases. Each PPG pulse in a given data is then expressed as a sum of these Gaussian functions as shown in Figure 2.

1) PPG as sum of Gaussian functions: A Gaussian function is characterised by its mean, standard deviation and amplitude. The mean of the systolic phase component is placed around the systolic peak and that of the diastolic phase component is placed around the diastolic peak. The parameters of these Gaussian functions are optimized to minimise the error of approximation.

Each pulse $p_i(n)$ is expressed as

$$p_i(n) = \hat{p}_i(n) + e_i(n) = S_i(n) + D_i(n) + e_i(n) \qquad (4)$$

where $\hat{p}_i(n)$ is the approximated Gaussian fit for the original pulse, $p_i(n)$, $S_i(n)$ and $D_i(n)$ represent the Gaussian functions for systolic and diastolic phases respectively and

Feature	Threshold Range	PQI Degradation
$a_{S,i}, b_{S,i}$	$> 1.5x$ *or* $< 0.5x$	30%
y_i	$> 3x$ *or* $< 0.3x$	30%
$c_{S,i}$	$> 3x$ *or* $< 0.3x$	30%
r_i	$> 10x$	30%
$a_{D,i}, b_{D,i}, c_{D,i}$	$> 3x$ *or* $< 0.3x$	20%
z_i	> 3	10%

TABLE I: Feature wise degradation in Pulse Quality Index

$e_i(n)$ is the remaining error which is insignificant and is hence neglected. Expanding the Gaussian functions, we have

$$\hat{p}_i(n) = a_{S,i} \cdot exp(-\frac{(n-b_{S,i})^2}{2 \cdot c_{S,i}^2}) + a_{D,i} \cdot exp(-\frac{(n-b_{D,i})^2}{2 \cdot c_{D,i}^2}) \quad (5)$$

where $a_{S,i}, b_{S,i}, c_{S,i}$ denote the Gaussian coefficients for the systolic phase and $a_{D,i}, b_{D,i}, c_{D,i}$ denote the Gaussian coefficients for the diastolic phase.

D. Number of peaks

The normal cardiac pulse cycle consists of at most two peaks, a systolic peak and a diastolic peak. Other peaks than these two can be attributed to artifacts. The number of local peaks, z_i are calculated using the approximated Gaussian fit, $\hat{p}_i(n)$.

E. Quality and Heart Rate Estimation

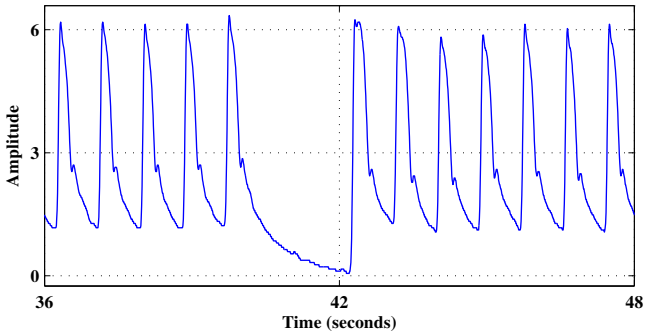
The feature vector for each pulse is constructed using the parameters obtained in previous discussion. The feature vector consists of Gaussian fit parameters, spectral residual for each pulse, number of local peaks within the pulse and pulse amplitude. As this technique is aimed at arrhythmia detection, pulse width is not used as a feature. The features are then median normalized over a window of 30 pulses.

Each pulse is assigned a quality index (PQI) of 100. PQI is reduced if the feature values exceed certain threshold. The degree of degradation in quality index and the threshold can be varied per feature. Gaussian coefficients for the systolic phase of the pulse, amplitude value, residual value are given higher weight as they contain higher information about pulse shape. In turn, the penalty for exceeding thresholds of these features is also the higher. Other features like diastolic phase coefficients, number of local peaks are given lower priority. A final threshold is required to categorize a given pulse as valid or artifact.

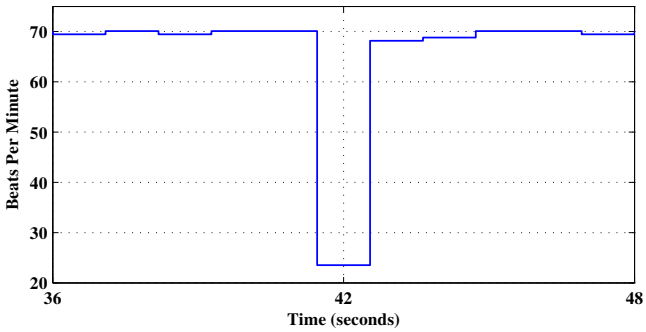
Capnobase data [8] is used to select appropriate values of individual feature thresholds as well as final threshold to distinguish between valid pulse and artifact. Optimized thresholds are shown in Table I. The final threshold is set at $PQI = 60\%$. The thresholds are adjusted in order to maximize accuracy for pulse rate segmentation and heart rate estimation. All pulses with $PQI > 60\%$ are used to estimate instantaneous heart rate.

V. ARRHYTHMIA DETECTION

Final step is detecting possible arrhythmia from the PPG signal. The aim of the work is arrhythmia detection, thus no knowledge regarding the location of the alarm is used in this analysis. Whole PPG recording is processed for detection. Following definitions are used for detection.



(a) Input PPG signal containing Asystole event



(b) Estimated pulse rate

Fig. 3: Asystole alarm detection using PPG. Pulse rate less than 30bpm indicates presence of asystole event.

1) Tachycardia (TA): Heart rate of more than 100 for 5 consecutive pulses.
2) Bradycardia (BA): Heart rate of less than 60 for 5 consecutive pulses.
3) Asystole (AS): No heartbeat for 2 seconds or heart rate less than 30.
4) Ventricular Tachycardia (VTA): Mean heart rate of more than 100 for 5 consecutive pulses.
5) Ventricular Fibrillation (VFB): Heart rate of more than 200.

Definitions used for TA and VTA are similar. Again, the focus here being arrhythmia detection, classification between the tachycardias is not performed.

VI. RESULTS AND DISCUSSION

For a PPG signal to be used for arrhythmia detection, the overall quality index for that signal must be greater than 60% i.e. at least 60% of total pulses must be artifact-free. Of the total 628 PPG signals available, 569 recordings qualified the quality criteria and were used for detection. The rejected signals primarily suffer from sensor disconnection and no information about heart rate can be obtained from them. The performance was evaluated using three metrics, (i) true positive rate (TPR) indicating how many (percent of) true alarms are detected, (ii) true negative rate (TNR), indicating how many (percent of) false alarms were removed, (iii) $Score = 100*(TP+TN)/(TP+TN+FP+5*FN)$ which

Reference	Type of arrhythmia														
	AS			TA			BA			VTA			VFB		
	TPR	TNR	Score	TPR	TNR	Score	TPR	TNR	Score	TPR	TNR	Score	TPR	TNR	Score
[9]	100	97	97.4	97	100	87.8	100	72	83.5	85	84	75	67	100	78.57
[10]	92	78	76.4	96	60	80.00	96	66	73.5	93	65	67.4	83	88	79.6
[11]	56	94	74.3	100	100	100.00	100	57	74.2	90	71	68.9	67	92	72.9
[12]	85	88	79.6	99	89	96.38	96	79	83	84	74	66.3	75	94	87.3
[13]	100	86	NA	100	89	NA	100	93	NA	84	85	NA	100	65	NA
Proposed method	85.7	95.2	90.5	97.6	77.7	88.2	88.8	73.1	66	88.1	30.7	39.4	50	61.3	48.8

TABLE II: Results for PhysioNet Challenge dataset

is defined by the PhysioNet challenge. The score weighs false negative alarms much higher than false positives. Performance metrics are compared with top entries of the challenge. These entries utilise ECG, PPG and ABP signals to suppress false alarms. (i) **TA**: High TPR rate was obtained for TA alarms. The dataset contained only 7 false alarms of which the technique was able to remove 6, resulting in lower TNR. However, the overall score for TA was observed to be higher. (ii) **BA**: High TPR rate was obtained for BA alarms as well. TNR was lower compared to TPR which subsequently lowered the overall score as well. (iii) **AS**: Asystole data had many low quality signals which reduced the number of useful signals. However, the TPR, TNR and overall score were all very high for AS alarms. An asystole event and corresponding heart rate are shown in Figure 3. (iv) **VTA**: VTA alarms also had a very good TPR. However TNR was very low. VTA is characterized by ventricular heartbeats with heart rate over 100 bpm and differs from TA alarms. These ventricular heartbeats can be identified through ECG much more effectively than PPG. Here, VTA is identified through instantaneous heart rate alone, not observing where the beats are originating from. This led to high TPR but poor TNR as the method incorrectly classified many signals with high pulse rate as VTA alarm. (v) **VFB**: The data contained only 6 true VFB alarms of which only 4 were useful. The technique could identify 2 of the 4 correctly. TNR was little better, however like VTA alarms, VFB alarms also better processed through ECG. To summarise, TPR of above 85% was achieved for 4 types of arrhythmias and TNR above 70% was achieved for 3 types. Out of total 199 true alarms, 185 were detected achieving TPR of 93% and out of 370 false alarms, 199 were rejected with overall TNR of 53.78%. VTA alarms contribute most in lowering the overall TNR as TNR of 82.42% is achieved for remaining 4 arrhythmias. The performance of this technique was comparable with other top entries submitted to the challenge except in cases of VTA and VFB where ECG processing has clear advantage. Overall, the technique has been able to address the issue of very high false alarm rate usually produced by bedside monitoring units in hospitals.

VII. CONCLUSIONS

This work is aimed at extending the idea of PhysioNet Challenge 2015 and using PPG signals to detect arrhythmia alarms and not just suppress false alarms. A new pulse quality index is developed to estimate the quality of individual pulses and overall signal. Gaussian curve fitting is used to express a PPG pulse. These Gaussian coefficients along with other morphological features are used to remove artifacts and estimate heart rate. Instantaneous heart rate is used to detect arrhythmia. PhysioNet Challenge training data is used for analysis. The data contained five types of arrhythmia including tachycardia, bradycardia, asystole, ventricular tachycardia and ventricular fibrillation. An overall true positive rate of 93% has been achieved with true negative rate of 53.78%. The high TPR indicates that PPG is a viable alternative for arrhythmia detection.

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