CardioFit: Affordable Cardiac Healthcare Analytics for Clinical Utility Enhancement

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Abstract. In this paper, we present CardioFit, a completely noninvasive cardiac condition monitoring system that enhances the clinical utility of health care analytics like lowering false detection of cardiac arrhythmia condition, higher accuracy in heart rate variability (HRV) computation. It performs powerful local analysis to enable accurate as well as easy-to-use, round-the-clock in-house, remote or mobile cardiac health checking. Here, photoplethysmogram (PPG) is the sole physiological signal considered for cardiac health management. It is to be noted that PPG carries significant necessary features what is available from electrocardiogram (ECG) signal. Unlike ECG, extraction of PPG is noninvasive, easy and affordable using smartphone or other low cost sensors. However, PPG is frequently contaminated with various kinds of motion artifacts and noise. Our robust concoction of signal processing and machine learning techniques exhibit higher accuracy in the detection and removal of the corrupt PPG signal segments. The proposed mechanism substantially improves the detection capability of the cardiac condition. Efficacy of our scheme is depicted using publicly available MIT-Physionet database as well as through our own field-collected real-life PPG data.

1 Introduction, Motivation and Contribution

Cardio-vascular disease is one of the biggest killers as per American Heart Association [1]. However, cardio-vascular diseases are preventable and early detection would effectively avert untimely human life loss. There are number of challenges that need to be overcome for delivering less error-prone cardiac condition detection. First of all, PPG extracted through smartphone, pulse oximeter or wearable sensor is often corrupted with ambient noise, motion artifacts and other noise sources. Even the warning systems in hospital ICU (Intensive Care Unit) are prone to transient noise [2], which leads to high number of false alarms [2, 3]. In fact, high false negatives (higher undetected cardiac conditions) would be deadly to the patients [4].

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We claim that our proposed method, CardioFit has the potential to eliminate the corrupt PPG segments with higher accuracy that minimizes the false negatives in the decision process. Another advantage is that the infrastructure requirement of CardioFit is nominal (only smart phone or other smart wearables suffice) and due to its completeness with local analytics, users can check health condition locally and can consult specialists remotely whenever required. Novelty of our proposed scheme is to reduce the number of false alarms in the detection of cardiac anomaly conditions like arrhythmia to a larger extent. Our uniqueness of the proposed scheme is that we analyze only PPG signal to interpret the heart condition whereas most of the state-of-the art solutions consider ECG, arterial blood pressure (ABP), and other pressure signals along with PPG [4–6]. CardioFit enhances the clinical utility significantly through effective corruption removal from PPG. Our method consists of supervised machine learning along with biomedical signal processing and information theoretic techniques. We use Morphologically Adaptable Dynamic Time Warping (MADTW), similarity based morphological pattern analysis for detecting and removing the corrupted signal segments [8]. It helps to detect an efficient and effective cardiac health monitoring like arrhythmia estimation and classification, accurate heart rate variability computation. CardioFit is sufficiently generic for implementing in wearable sensors, smart watches, smart phones, PC workstations, ICU monitors and ambulances; wherever PPG signal is available.

We organize our paper as follows. In Sect. 2, we describe the system architecture and present the CardioFit scheme and algorithms. The results demonstrating the efficacy of our proposed scheme are presented in Sect. 3. Finally, we conclude in Sect. 4.

2 CardioFit: Scheme and Algorithms

CardioFit consists of five main functional blocks: 1. *Raw PPG signal extraction*: It is done using smart phones, pulse oximeter or other sensors, [7] 2. *Multistage decorruption*: Mono-signal PPG corruption detection and elimination, 3. *Cardiac-parameter extraction*: Heart Rate (HR) is extracted using robust signal processing technique [8], 4. *Statistical Analysis*: To investigate the statistical trend of the cardiac-parameters for cardiac abnormality, 5. *Decision*: To decide the normality and abnormality of the heart condition along with detecting arrhythmia aiming low false negative alarms.

PPG signals extracted from smart phones or other wearables contain high amount of corruption particularly due to motion artifacts. Directly processing such noisy and corrupted signal invariably results in false alarms. In order to minimize such false alarms, we propose multi-stage decorruption.

2.1 Multi-stage Decorruption of PPG Signal

We classify the corruption in PPG as: 1. Extremas and 2. Intricates, where extremas are the corruptions due to larger, transient disturbance and intricates are due to smaller, mostly prolonged disturbances as shown in Fig. 1.

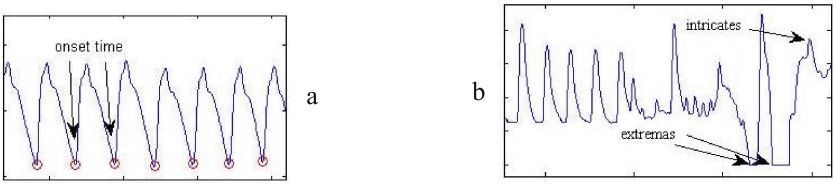

Fig. 1. PPG signal (a), ideal or expected, (b) as extracted from camera or other sensors

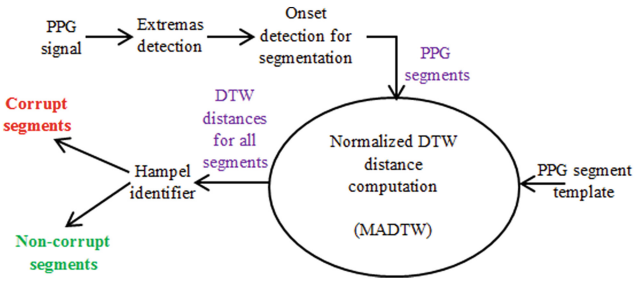

Fig. 2. Complete process of our proposed CardioFit multistage PPG decorruption

Extrema detection. We apply extreme value statistics and consider modified Thompson Tau technique [11, 17], to statistically find the extremas.

Intricate detection. PPG signal consists of series of segments $\Omega_k, k = 1, 2, \ldots K$ and each segment (Fig. 1a) identifies a single complete heart beat. Segmentation or pulse period detection of PPG signal is achieved by identifying the onset times through slope-adjusting and realigning through weighted slope sum function (SSF) [9]. In order to compute the intricate corruptions in each PPG segment Ω_k, Dynamic Time Warping (DTW) with modification (Morphologically Adaptable DTW (MADTW)) is applied. We normalize each segment as $\Omega_k \rightarrow \Omega_k \times \frac{max(\mathbb{T})}{max(\Omega_k)}$, where $\mathbb{T}$ is a typical PPG segment template, following the derivation of the most probable segment length [8, 15]. DTW distance $\delta_{\Omega_k,\mathbb{T}}$ is computed between the PPG segment template $\mathbb{T} = \{t_1, t_2, \ldots, t_M\}$ of length M and normalized segments $\Omega_k = \{\omega_1, \omega_2, \ldots, \omega_{l_p}\}_k, k \in K$ of the extracted PPG segments as:

$$\begin{aligned}\delta_{\Omega_k,\mathbb{T}} &= \delta\left(\left[\omega_1, \omega_2, \ldots, \omega_{l_p}\right], [t_1, t_2, \ldots, t_M]\right) \\ &= \mathcal{D}\left(\omega_{l_p}, t_M\right) + min\begin{cases}\left(\left[\omega_1, \omega_2, \ldots, \omega_{l_{p-1}}\right], [t_1, t_2, \ldots, t_{M-1}]\right) \\ \left(\left[\omega_1, \omega_2, \ldots, \omega_{l_{p-1}}\right], [t_1, t_2, \ldots, t_M]\right)\end{cases}\end{aligned}$$

where, $\mathcal{D}(\omega, t) = Eucl(\omega, t) := \sqrt{\sum_{i=1}^{N}(\omega_i - t_i)^2}$, $\delta_{\Omega_k,\mathbb{T}}\big|_{corrupt}(\approx 7.8) \gg \delta_{\Omega_k,\mathbb{T}}\big|_{normal}(\approx 1.5)$.

We apply Hampel filter [10, 14] on the computed DTW distances of each PPG segment $(\delta_{\Omega_k,\mathbb{T}}), k = 1, 2, 3, \ldots$. When Hampel identifier declares certain DTW distances among $\delta_{\Omega_k,\mathbb{T}}$ outlier, the corresponding PPG segment(s) is declared as corrupt. Proposed multistage decorruption technique of PPG is shown in Fig. 2.

3 Experimental Methodology and Results

We have collected real-field PPG data from 10 healthy subjects with uniform distribution (5 males and 5 females) through pulse-oximeter by controlled experiments like five different motion artifacts (a. finger twist, b. light hand movement, c. medium hand movement, d. hard hand movement, e. body movement) to simulate the near real-life noise and artifacts, which are annotated as shown in Fig. 3. First we validate our proposed corruption removal method on this real-field PPG signal. In Fig. 4, we illustrate an exemplary scenario of corruption detection on real-field data. We have also performed extensive experiments with publicly available MIT-Physionet data [13], where the annotations are made through a majority voting process. In Table 1, we depict the overall average performance merit of both real-field as well as MIT-Physionet data in terms of precision $= \frac{TP}{TP+FP}$, recall $= \frac{TP}{TP+FN}$, and specificity $= \frac{TN}{TN+FP}$, where TP, TN, FN, FP = Total number of true positives, true negatives, false negatives, false positives respectively.

We compare the performance of CardioFit with standard method (SM), the method that does not execute corruption removal as shown in Fig. 5, where PPG signals with 5 types of motion artifacts are considered. First, we show that the computation of HRV (Heart Rate Variability), an important cardiac health marker does not vary much from ground truth (HRV derived from uncorrupted PPG) while comparing CardioFit against standard method (Fig. 6). HRV is calculated by SDNN method which is the standard deviation of NN intervals (beat-to-beat interval) [12]. We observe that Mean Absolute Deviation (MAD) with respect to ground truth of HRV computation for CardioFit = 0.34, whereas for standard method it is =36.5. It is to be noted that standard

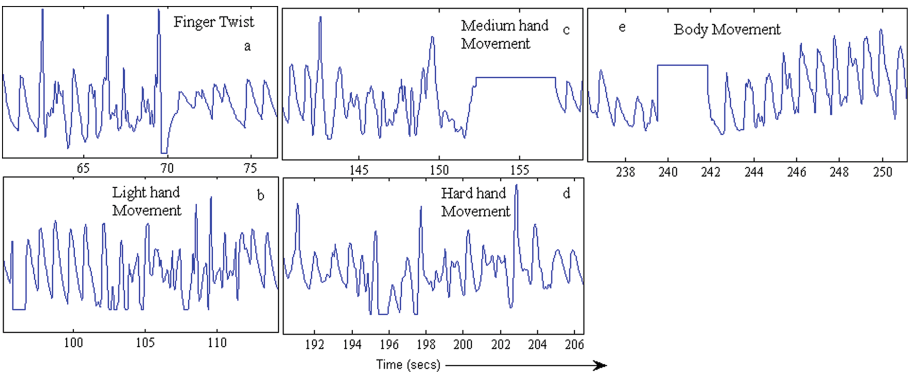

Fig. 3. Different kinds of artifacts (showing five different artifacts) in PPG signal

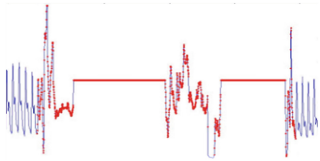

Fig. 4. Corrupt PPG segment (marked red) detection from real field PPG data (Color figure online)

Table 1. Corruption detection performance on MIT-Physionet

Performance metric	Value (%)
Recall	80.4
Specificity	96.4

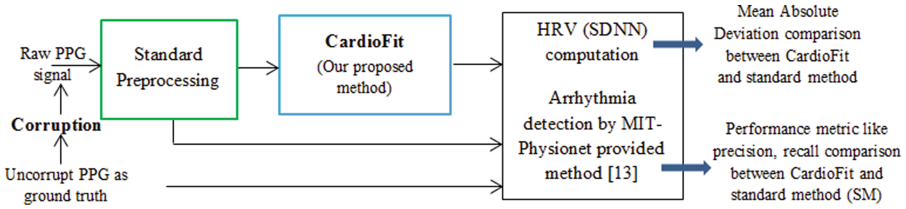

Fig. 5. Performance comparison method between CardioFit and standard method

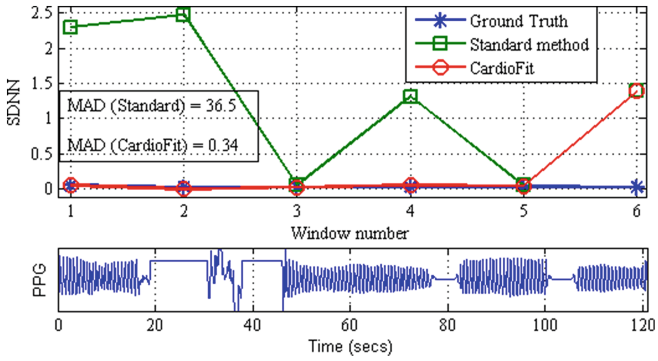

Fig. 6. HRV computation efficacy of CardioFit

preprocessing consists of 1 Hz drift suppression, followed by 30 Hz Low pass filtering with 0.5–4 Hz band pass filtering.

We experimented with MIT-Physionet challenge 2015 datasets with arrhythmia annotations and basic arrhythmia detection algorithm [13]. We demonstrate the performance of detection of bradycardia as shown in Table 2. We find that false negatives

Table 2. Cardiac arrhythmia (bradycardia) detection performance comparison

Performance metric (%)	SM (Bradycardia)	CardioFit (Bradycardia) [8]
Precision	66	62
Recall	97	100

from CardioFit are consistently proved to be very low (i.e. recall is very high $\rightarrow$ 100%), with comparable precision value [8].

4 Future Works and Conclusion

Our effort is to bring a newer dimension in cardiac-signal analytics with robust machine learning, signal processing, and statistical analysis based algorithms. We endeavor to contribute for minimization of the errors in the diagnosis of cardiac-related diseases that arise owing to the corruption in the physiological signals like PPG derived from smartphone and other affordable sensing devices. We claim that the novel de-corrupting techniques applied on PPG signals have the potential to minimize the false detection of cardiac abnormality conditions that ensures significant clinical utility enhancement. Thus, we establish CardioFit as an affordable, easy-to-use cardiac healthcare analytics tool. We endeavor to extend CardioFit to include other related cardiovascular diseases like angina and myocardial infarction, cardiomyopathy, congenital heart failure etc., along with robust feature detection [16].

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