Cardiac Condition Monitoring through Photoplethysmogram Signal Denoising using Wearables: Can We Detect Coronary Artery Disease with Higher Performance Efficacy?

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Abstract

For affordable cardiac health monitoring, it is required to ensure accurate cardiac condition detection from smartphone or wearable-extracted photoplethysmogram (PPG) signals through precise identification, and removal of signal corruption. Presence of noise particularly due to motion artifacts strongly impacts the outcome of analysis. We establish that denoising of PPG signal would pave ways for better clinical prediction than analyzing the signal in presence of noise. In this paper, we prove that analyzing on cleaned (denoised) PPG signal yields significant performance efficacy improvement while performing Coronary Artery Disease (CAD) identification. The proposed method is independent on the clinical analytics and CAD detection is considered to be a use case to justify our claim that physiological signal pre-processing, specifically denoising can substantially improve the overall performance effectiveness and clinical utility.

1. Introduction

It is perceived that preventive, round-the-clock healthcare management is one of the near-future certainties and this is becoming realistic due to the ubiquity of smartphones, and wearables, cheaper storage, highly powerful edge-processors. However, different aspects like security, privacy, quality of service guarantees while capturing and processing the sensitive data like health parameters are to be addressed [5, 9, 13, 14] along with building precise sensors and analytics solution.

Cardio-vascular disease is one of the biggest killers of human history and one adult American die about every 40 seconds due to cardio-vascular diseases as per the American Heart Association [2]. We endeavour to enable affordable, non-invasive cardiac management (initially with basic functionalities) through smartphones and wearables. PPG is a basic, but important indicator of cardiac health that can be extracted directly from smartphones or low cost device like pulse oximeter. Apart from measuring heart rate, heart rate variability, SpO2, many sophisticated analytics can be done through PPG signal. In this paper, we consider whether CAD can be detected from PPG signal with high performance efficacy.

However, it is found that analytics over PPG signal suffers from higher amount of false alarms particularly due to the presence of ambient, transient noise, various motion artifacts [3]. A good amount of research is focused on the detection and correction of corruption in PPG signal, but it is still a major challenge. In this paper, we propose a multi-stage PPG signal noise identification and elimination method. We also illustrate that denoising of PPG signal and clinical analytics on clean PPG signal yield better accuracy and less false alarms. Hitherto, we establish that clinical utility of our noise cleaning method would provide substantial benefit for ensuring less error prone clinical analytics and can impact the trigger of subsequent medical attention.

2. State-of-the-art

The field of noisy physiological signal analysis is a major concern of researchers, particularly noise removal form PPG signal [4 – 6]. There are different types of approaches. Authors in [15] used Support Vector Machine (SVM) based classifier for noise classification. In [7], multi-signal analysis (combination of PPG, Electrocardiogram (ECG), and Arterial Blood Pressure (ABP)) has been performed. But in smartphone or in-house setup, it is impractical to analyse on ECG or ABP which are invasive and require costly infrastructure. Our main contribution is mono-signal analysis, i.e. PPG is the sole signal considered to carry out the analysis, which is rather expected in building applications in smartphones. PPG-only signal denoising with signal quality estimation is presented in [8]. However, this scheme is computationally expensive with higher order machine learning processes and multivariate 'voting' threshold

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mechanisms. Such method is still not practically implementable or realistic in smartphone-based clinical assessment scenario and would hardly provide real-time performance.

3. Our proposed algorithm

We propose multi-stage method for detecting the presence of noise in PPG signal. Input PPG P_s signal is segmented using slope sum function [1]. From the segment set Ω_k, the most probable segment duration l_p is computed using DBSCAN clustering.

We compute the dissimilarity measures using dynamic time warping (DTW) distances $\delta_{\Omega_k,\mathbb{T}}$ between an ideal PPG segment template $\mathbb{T}$ and $\Omega_k \rightarrow \Omega_k = \left\{\omega_1, \omega_2, \dots, \omega_{l_p}\right\}_k$, i.e. each segment is restricted to l_p to counter non-linearity of PPG segments.

Subsequently, Hampel filter, a standard outlier detection method is applied on the computed $\delta_{\Omega_k,\mathbb{T}}$. The detected outliers in the DTW distances are declared as corruption. PPG segments corresponding to the DTW distances that are declared outliers are considered to be noisy segments. We then remove those noisy segments from the PPG signal and the obtained clean PPG signal is used for clinical analysis like CAD detection.

Below in table 1, we provide the brief description of the notations commonly used throughout this paper. Next, we describe the components in detail.

Table 1. Notation and meaning

Notation	Meaning
P_s	PPG signal time-series
Ω_k	k^{th} PPG segment, k= 1,2, …K
ω_i	i^{th} sample point of a PPG segment Ω_k
Ω_k^N	Normalized k^{th} PPG segment
$\mathbb{T}$	Ideal PPG segment template
$\delta_{\Omega_k,\mathbb{T}}$	DTW distance between Ω_k and $\mathbb{T}$
l_p	Most probable segment length

3.1. Analysis on PPG segmentation

PPG is a quasi-periodic physiological signal, where the periodicity indicates heart rate and the signal consists of time-series of segments as shown in figure 1. Each of the segments signifies one complete heart cycle consisting of systole and diastole events.

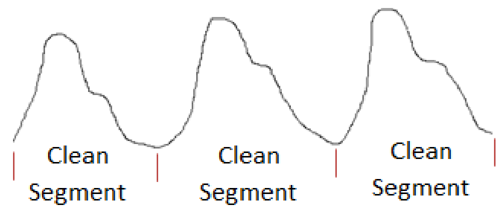

Figure 1. Segmentation in clean PPG signal.

However, in noisy PPG signals, at least few of the segments would be corrupted and extremely distorted as shown in figure 2. Our proposed method finds the presence of such distorted PPG segments that correspond to presence of noise (with high probability). In fact, each clean PPG segment corresponds to one complete heart cycle.

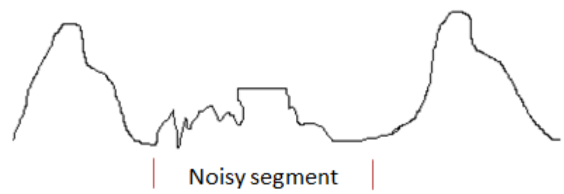

Figure 2. Presence of noisy segment in noisy PPG signal.

In order to find the noisy segments, we require to segmentize the PCG signal $\mathrm{P_s}$. The segments $\Omega_\mathrm{k}, \mathrm{k} = 1,2, \dots, \mathrm{K}$ are derived using slope sum function. First the PPG signal is filtered with narrow band pass filter and the filtered PPG is slope-adjusted and realigned through weighted slope sum function [1] to find the series of $\Omega_\mathrm{k}, \mathrm{k} = 1,2, \dots, \mathrm{K}$, where K is the total number of complete heart cycles present in $\mathrm{P_s}$. Let $l_k,\ k = 1,2, \dots, K$ be the segment length of Ω_k. But the length is highly varying even for clean PPG extracted from a normal subject. In order to eliminate this non-linearity, we find the most probable segment length l_p [6].

Height of the systole peak is also variable and needs to be normalized. The normalized PPG segment (Ω_k^N) is derived as:

$$\Omega_k^N = \frac{\mathbb{T} \times \Omega_\mathrm{k}}{max(\Omega_\mathrm{k},\ \forall k)}, k = 1,2, \dots, K$$

3.2. Feature extraction for dissimilarity measure

We compute the dissimilarity $\delta_{\Omega_k,\mathbb{T}}$ of each segment from the given ideal template $\mathbb{T}$ by computing DTW distance between $\mathbb{T}$ and Ω_k^N, k=1,2, …, K.

DTW is a non-linear, elastic optimal alignment technique to compute the optimal alignment or (di)similarity between the ideal template and each of the PPG segment [3, 6, 11]. For a noisy PPG segment, DTW distance of corresponding PPG segment is substantially higher than a clean segment.

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 (may be close to normal heart rate 72 beats per minutes, if f_s be the sampling frequency, M consists of $1.2 \times fs$ number of samples) and normalized segments $\Omega_k^N = \left\{\omega_1, \omega_2, \ldots, \omega_{l_p}\right\}_k^N$, $k \in K$ of each the normalized extracted PPG segments as [3, 6, 10, 11].

3.3. Outlier detection for noisy segment identification

Outlier detection is an interesting research method applied to various domains [14]. Given a series of $\delta_{\Omega_k,\mathbb{T}}$, the challenge we face is to distinctly differentiate noisy and clean segments. In a typical PPG signal, the set of $\delta_{\Omega_k,\mathbb{T}}\big|_{noisy}$ is outlier in the complete set of $\delta_{\Omega_k,\mathbb{T}}$.

We employ Hampel filter based outlier detection method over the complete set of $\delta_{\Omega_k,\mathbb{T}}$ to detect the outliers. As the noisy PPG signal, most probably contain more than one noise segments, either masking or swamping effects would impact the detection method to produce inaccurate decision. When masking effect predominates, number of outlier points gets undetected, while swamping effect is heavy, normal observations are often inferred as outliers. Our goal is to minimize the masking effect, so that outlier points (i.e. $\delta_{\Omega_k,\mathbb{T}}\big|_{noisy}$) relates to the noisy segment, do not get undetected. Hampel filter is a nonlinear outlier detection filter that minimizes the masking effect [13].

3.4. Clinical utility assessment: CAD detection

CAD is a life threatening cardio-vascular disease. PPG bears significant information of cardiac condition and the signature of CAD can be present in PPG signal.

There are two important cardiac features, heart rate (HR) and heart rate variability (HRV) can be extracted from PPG signal with higher accuracy. There are different methods by which HRV can be computed like RMSSD ("root mean square of successive differences"), SDSD ("standard deviation of successive differences") etc. We derive standard deviation of NN intervals–based HRV, which is extracted from 20 second non-overlapping windows.

For classification purpose, we consider linear kernel based Support Vector Machine Classifier, where HR and HRV are the features. In figure 3, we show the CAD classification process for clean and unclean PPG signal.

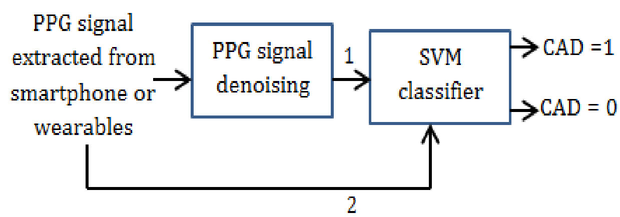

Figure 3. CAD classification with and without PPG signal denoising. Here '1' means clean PPG signal and '2' means unclean/ unprocessed PPG signal (PPG signal bypassing the denoising process).

4. Results

Our main contribution is effective denoising of PPG signal and then to establish that analysis on PPG signal (few consider CAD detection in this paper) after noisy components removal yield significant performance gain. Our first set of results show that the proposed PPG denoising is highly effective with significant accuracy as shown in figure 4. Secondly, we depict that clinical utility, i.e. analysis for medical inference on clean PPG signal results in higher performance efficacy.

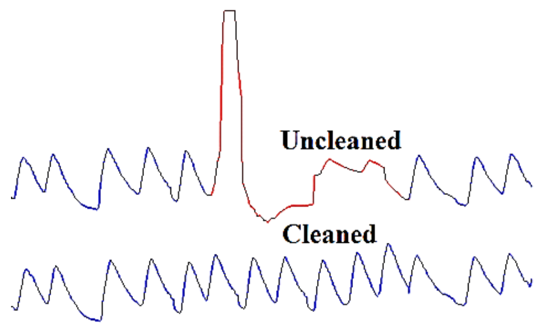

Figure 4. Detection of uncleaned/noisy PPG signal segment.

We experimented with 10 real-field and 10 MIMICII Physionet Challenge 2015 PPG datasets, each of approximately 5 minute duration. First, we depict the efficacy of the proposed method to detect the corrupted PPG segments. Next, we show that removing those corrupt segments result in clean PPG signal and analyzing on clean PPG signal results in more accuracy in CAD detection, i.e. higher clinical utility is achieved.

4.1. PPG signal corruption detection efficacy

We achieved PPG corruption detection performance efficacy as depicted in Table 2.

Table 2. Performance efficacy of multi-stage PPG denoising algorithm

Performance measure	Real-field	MIMC-II
Recall	79%	80.4%
Specificity	97.4%	96.3%
Precision	89.4%	72%
F1	0.84	0.76

4.2. Clinical utility: CAD detection efficacy

We considered 126 PPG datasets from MIMCII with 67 CAD and 59 Normal subjects; training dataset: 40 CAD, 30 Normal; test dataset: 27 CAD, 29 Normal subjects. One set of PPG signals passed through our proposed denoising processing and in another case that process is bypassed. Both types of PPG signals (Processed/ cleaned and raw/ unprocessed) are fed to the SVM classifier as depicted in figure 4. When CAD is detected by the classifier, classifier out = 1, else = 0. We observed high performance efficacy of CAD detection when cleaned PPG are used for analysis. The result is depicted in Table 3.

Table 3. Performance efficacy demonstrating the clinical utility

PPG Signal type	Performance Measure		
	Precision	Recall	F1
Clean	51.11%	79.31%	.62
Unclean	43.59%	58.62%	.49

In fact, we have shown previously in our contribution in [10] that HRV computation is significantly accurate while investigating on clean PPG. This result further strengthens our claim of pre-processing efficacy. We have also demonstrated that effective denoising results in higher accuracy in detecting cardiac arrhythmia in our earlier works [3, 6].

5. Conclusion

Cardiac health management at the ease of fingertip is a reality. In this paper, we have demonstrated that PPG based cardiac health supervision through smartphones or wearable sensors have the potential to achieve high accuracy with fewer false alarms. Appropriately pre-processed PPG signal would return higher clinical utility as we have established that CAD detection from PPG signal is much more accurate when our proposed denoising process is part of pre-processing chain.

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