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Developing a Novel Noise Artifact Detection Algorithm for Smartphone PPG Signals: Preliminary Results*

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Abstract— **Pulsatile signals recorded from a smartphone are often corrupted with noise artifacts, which hampers accuracy of the peak detection and consequently leads to inaccurate heart rate estimation. In this paper, we propose a novel approach which uses an algorithm based on variable frequency complex demodulation (VFCDM) to detect noise artifacts in the smartphone's pulsatile signal recorded from a fingertip video. The ultimate goal is to increase the accuracy of atrial fibrillation (AF) detection. In the time-frequency spectra obtained from VFCDM, thresholds are imposed on both the magnitude of the dominant frequency component at each time instant and on the successive difference of the significant frequency component in the heart rate range to enable accurate noise artifact detection. For this preliminary analysis, the performance of the proposed method has been evaluated on 200 subjects; the data were collected during a smartphone-based AF screening study in India. The proposed method is shown to detect noise artifacts in pulsatile signals with 91.16% accuracy, demonstrating the potential to reduce false alarms when only data segments identified as clean are used for AF detection.**

I. Introduction

Smartphones are becoming ever more popular, giving us a novel opportunity to process and transmit clinically-relevant data from their various sensors, in real time. Health monitoring using smartphones has gained much attention as there is an increase in interest in moving from point-of-care devices to mobile health monitoring [1]. Without the need for any additional hardware, smartphones become a relatively low cost physiological monitoring system and a take-anywhere device for telemedicine applications.

One of the most promising applications of smartphone-based health monitoring is the use of a video photoplethysmogram (PPG), recorded by the smartphone's camera, to estimate the heart rate [2] and heart rate variability [3]. As proposed in [4], smartphone-based heart rhythm analysis can be used to detect atrial fibrillation (AF), which is the most common sustained arrhythmia and can increase the risk of stroke by fivefold if it is undetected [5]. Accurate detection of heart rate as well as AF from PPG signals largely depends on the recorded signal quality. However, in this study we have found that smartphone PPG suffers from unique noise artifacts due to the gap between the fingertip and the phone camera and also from displacement of the finger, causing sudden spikes, which lead to inaccurate heart rate estimation and misdetection of AF.

To combat this unique noise artifact problem, we have developed a time-frequency (TF) based noise artifact detection method for smartphone PPG signals. There are several works on detecting noise artifacts from PPG signals, but to the best of our knowledge, we are one of the first to address this problem for smartphone PPG signals. Noise artifact detection methods are usually based on calculating signal quality index (SQI) from waveform morphologies [6]. In [7], SQI is calculated using accelerometer and electrocardiogram (ECG) signals. Statistical measures like skewness and kurtosis with phase coupling are described in [8], while Shannon entropy along with Renyi's entropy is used in [9] to quantify SQI. However, frequency domain features are shown to be more robust than statistical features based on time-domain parameters in [10]. Variable frequency complex demodulation (VFCDM) is shown to achieve the best TF resolution along with accurate amplitude estimation when compared with continuous wavelet transform, smoothed pseudo-Wigner-Ville and Hilbert-Huang transform methods [11]. In [12], VFCDM is used to extract several features including noise power and projected frequency modulation difference from TF domain, and a support vector machine (SVM) is implemented to detect artifact and usable data from PPG signals. However, for smartphone PPG signals these features do not work well since PPG noise is different (contains sudden spikes due to gap and displacement) from standard PPG signals collected by pulse oximeters.

As a result, we present a novel noise artifact detection algorithm for smartphone PPG based on time-frequency spectra (TFS) obtained by VFCDM. This artifact detection method is based on dominant peak amplitude and successive difference of dominant frequency components. After noise artifact detection, the clean signals can be used for AF detection which is explored here with a linear SVM classifier.

II. Dataset Description

The smartphone-based AF screening study was performed in Anand district, Gujrat, India where 2000 people (men and women of 45 years and older) from 60 villages participated [13]. However, in this study we are showing preliminary results on portion of the originally acquired dataset, consisting of 200 people from 5 villages. A custom pulse-based iPhone app and a single-lead ECG recording were used to conduct the

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study where each individual was screened for atrial fibrillation three times. A single-lead ECG signal was recorded using an FDA-approved Alivecor device where each participant placed two or three fingers of their left and right hands on the two electrodes. Each subject was screened using the Alivecor device for 1 minute and then the iPhone app was used for 1 minute and 30 seconds. During the pulsatile signal acquisition from the iPhone, participants were asked to hold the smartphone in their hand, with their right first or second finger over the standard iPhone camera while the flashlight was turned on to illuminate the finger. Each ECG recording which was determined to be abnormal or AF by the Alivecor device was then subjected to review by two resident-level physicians independently as part of the adjudication process. If there was any disagreement between the reviews, a third fellow physician reviewed the ECG recording. After the pulse recording was over, standardized questionnaires including subjects' history, lifestyle, AF related symptoms, medications, and so forth, were collected. A detailed study protocol can be found in [13].

III. Method

A. Data Processing

The PPG signal was obtained by taking the average of 50×50 pixels of the green band for each video frame recorded by an iPhone 5 camera [14]. The sampling rate for the iPhone model used was 30 frames/second. Throughout this study, the PPG signal was divided into 30 second segments for AF detection. We wanted to examine if our AF algorithm retains its accuracy even for 30 second data segments. Each 30 second PPG segment was first bandpass filtered to 0.5-10 Hz using a 6th order zero-phase Butterworth filter, then detrended to remove any trends in the data, normalized by the maximum value of that window, and then the signal was changed to unit variance. The peak detection method implemented in this study includes a variable cut off frequency filter bank, spectral estimation of the heart rate, rank order nonlinear filters and decision logic as described in [15].

B. Noise Artifact Detection

During PPG signal recording using an iPhone, one needs to place the finger over the phone camera and lamp; the lamp illuminates the finger and the video is recorded by the camera. Based on the pixel variation with blood flow over the vein and arterial bed of a finger, a PPG signal is generated.

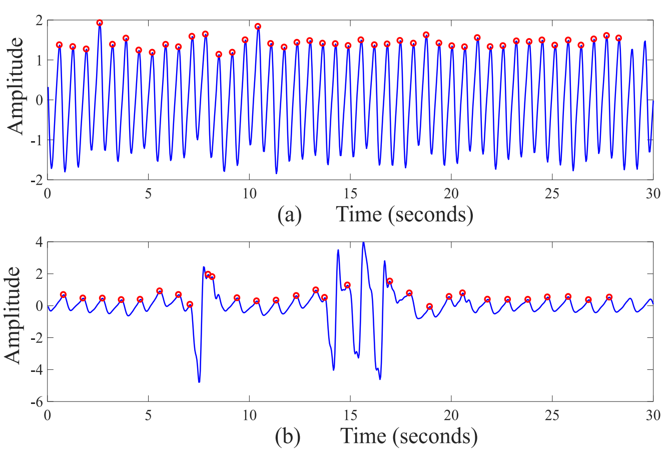

Figure 1. Sample PPG signal from iPhone: (a) clean signal and (b) corrupted signal.

However, if there is a gap between the finger and camera, the signal will be corrupted by noise artifacts, resulting in sudden increase in the amplitude of the PPG. Moreover, if the finger is moved unintentionally, it creates displacement and results in a corrupted signal of poor quality.

Fig. 1 shows samples of clean (top panel) and corrupted (bottom panel) 30 second PPG signals, and their detected peaks. Note the very different Y axis scales. It can be seen that for the clean PPG signal (top panel), peaks are detected correctly. However, in the case of the corrupted signal, sudden and very large changes of signal amplitude result in poor peak detection and eventually this will cause inaccurate heart rate estimation. Poor peak detection can lead to false positive AF detection because a normal rhythm can be determined to be an irregular rhythm due to inaccurate peak detection.

The preprocessed PPG signal is first used to determine whether a 30 second segment is corrupted by artifacts or not. To detect artifacts, VFCDM based time-frequency analysis has been implemented to differentiate spectral characteristics of the noise from clean PPG data at each time instant. The VFCDM method is applied to a signal for the estimation of the time-frequency spectrum (TFS). This process not only provides high time and frequency resolution, but also retains the amplitude distribution of the signal. The first step of the VFCDM involves obtaining the initial TFS estimate using fixed frequency complex demodulation (FFCDM) which was previously developed in our laboratory. In the next step, complex demodulation is performed using the center frequencies of the previously-obtained initial TFS, thus resulting in high-resolution based estimation of accurate TFS and its amplitudes. Since only the center frequencies are considered in subsequent analysis, VFCDM allows a significant improvement in computation time. Details of the VFCDM algorithm can be found in [11].

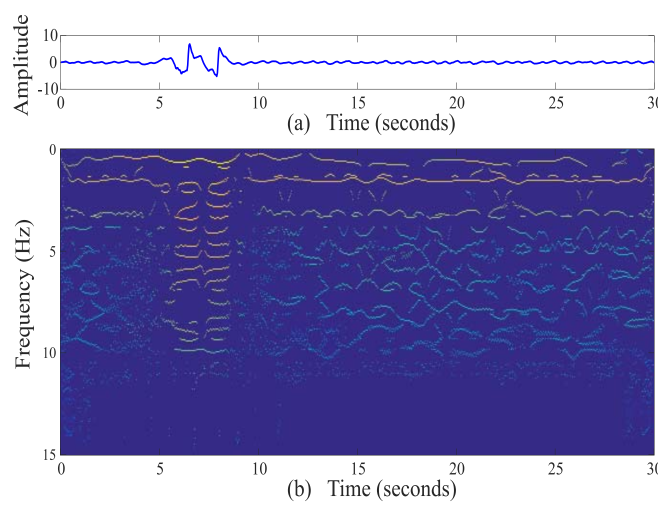

Figure 2. (a) Sample PPG signal; (b) Time frequency spectra of Fig. 2 (a) obtained by VFCDM.

Fig. 2(b) shows the time frequency spectra obtained by VFCDM from the PPG signal of Fig. 2(a). From the figure, it can be seen that TFS has different characteristics for the clean and corrupted signals. For the clean portion, the dominant frequency components (shown in yellow) in the heart rate range (0.5-3.5 Hz) are nearly continuous. However, for the corrupted part (~7- 9 second), there is discontinuity in the frequency amplitude. The reason is that noise artifacts distort the heart rate and its harmonics' traces in the TFS.

In this study, we have found that when there is an artifact or spike in the PPG signal due to a gap or displacement, not only do we get discontinuous frequencies in TFS, but also the associated amplitudes of the dominant frequency components in the heart rate range become larger compared to those of the clean portion. Fig. 3 represents this incident: Fig. 3(a) shows the frequency component amplitudes at a fixed time instant when the signal is corrupted. In other words, it represents a sample vertical line of the corrupted TFS shown in Fig. 2(b). Fig. 3(b) represents the dominant frequency peak amplitudes (DPA) for the entire 30 seconds of the PPG segment and TFS shown in Fig. 2(a) and Fig. 2(b), respectively.

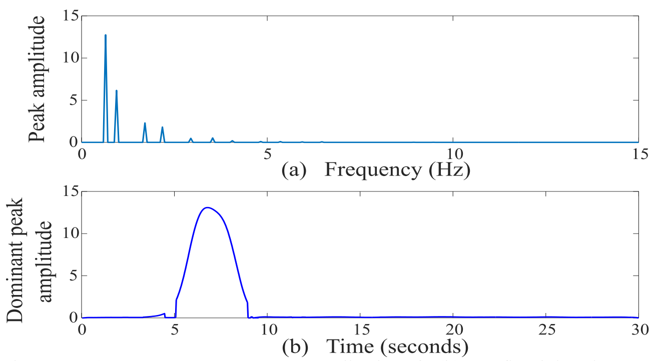

Figure 3. (a) Frequency component amplitudes of 2(b) at a fixed time instant; (b) dominant peak amplitudes (DPA) for the PPG segment shown in Fig. 2(a).

From the above figure, it can be hypothesized that setting a threshold on the dominant peak magnitude value can be used to detect noise artifacts. For our approach, we initially set two threshold values as shown in Eq. 1 (a-b). For example, as shown in Fig. 3b, if DPA is less than or equal to 1, we assume this is a clean signal whereas it DPA is greater than or equal to 4, we assign data to be corrupted. However, the above-noted threshold scheme is sometimes prone to detecting false positives, that is, detecting a clean portion of a PPG segment as noisy. This is due to the fact that, when there is an extra gap between the PPG peaks in the time domain, although the signal is not spiky, it shifts the frequency component magnitude value above the set threshold. To combat this problem for the moderately corrupted PPG segments, we impose another limit on the successive difference (DIFF) of the significant frequency component in the heart rate range due to the fact that heart rate does not change more than a certain limit at each time instant. So, the noise artifact detection logic becomes:

a) DPA<=1, PPG signal is clean.
b) DPA >=4, PPG signal is corrupted. (1)
c) 1< DPA <4 and DIFF >= 0.7, PPG is moderately corrupted.
d) 1< DPA <4 and DIFF< 0.7, PPG is clean.

Finally, based on these set threshold values, we provide graphical output as shown in Fig. 4(b), Fig. 4(d), and Fig. 4(f). In these plots, the values of "0", "0.5" and "1" indicate clean, moderately corrupted and corrupted, respectively. Fig. 4 shows representative noise artifact detection algorithm output on several PPG signals. From the figure it is visible that our proposed method works well for subjects with normal sinus rhythm (Fig. 4(a) and Fig. 4(c)) or AF (Fig. 4(e)).

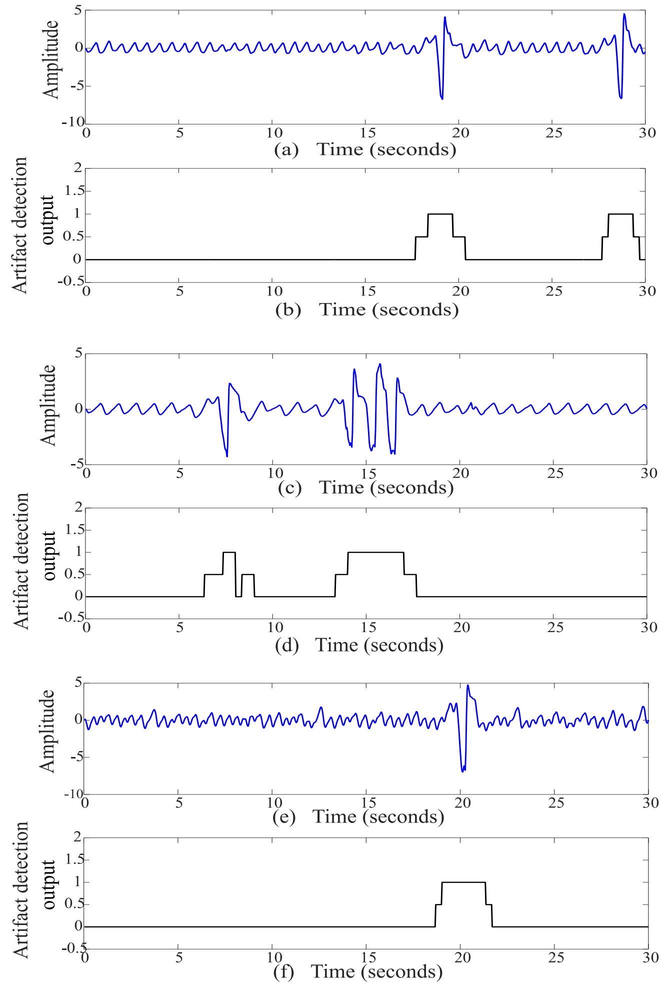

Figure 4. Noise artifact detection algorithm output for several PPG segments: (a)–(d) normal sinus rhythm; (e)-(f) AF segment.

Finally, we impose another condition for labelling a data segment either clean or corrupted. For a 30 second PPG segment, if the noise detection algorithm value is non-zero (i.e., either moderately corrupted or corrupted) for less than 3.5 seconds, the segment is regarded as a clean segment; otherwise the data segment is labelled as a corrupted segment.

IV. RESULTS AND DISCUSSIONS

In this preliminary study, smartphone PPG signals from 200 subjects collected from 5 villages have been analyzed. Among these subjects, 195 have normal sinus rhythm (NSR) while 5 have AF.

From these 200 subjects, we have 521 recordings from NSR subjects and 5 recordings from AF subjects, as some of the former had multiple recordings. From each recording, two 30 second segments were obtained, resulting in a total of 1 minute of PPG data for each recording. Thus, we have 526×2=1052 segments of 30 seconds of PPG. Using the proposed noise artifact detection algorithm, a 30 second segment was checked first to determine whether it was corrupted or not. If the 1 minute PPG (both 30 sec segments) was found clean, then we proceeded to the next step of AF prediction. For this, three features from the PPG intervals were used: root mean square of successive differences, Shannon entropy and sample entropy, as these features are shown to have discriminating properties to classify NSR and AF [4]. With these extracted features, a liner support vector machine (SVM) classifier has been designed to detect the irregular heart rhythms. SVM is a popular technique for classification tasks because of its efficiency and robustness to noise [16]. Since we have a small sample of AF subjects and a large number of NSR subjects in this preliminary study, we restricted our work to detecting the true negatives. The underlying assumption is that our noise artifact detection algorithm will discard the bad quality signals, resulting in accurate PPG peak detection and thus reducing the false alarms for AF.

The SVM was trained with 82 clean NSR segments (all from one village) and 10 AF segments (each segment being 30 seconds). The performance of the SVM was tested with 898 NSR segments collected from the rest of the 4 villages, each having 30 seconds of data. If the 1 minute of PPG was determined as AF (i.e., both 30 second segments of a particular recording), then that recording was diagnosed as AF. Similarly for NSR, if both 30 second PPGs were diagnosed as NSR segments, then the recording was treated as NSR. For all other cases, the algorithm decided that not enough clean signal was available to make a conclusive decision.

Without the noise detection algorithm, out of the 449 NSR test recordings (without the training 82 segments), the linear SVM misclassified 156 as AF. Certainly this supports the need for noise detection prior to AF detection. With our proposed noise artifact detection algorithm, 152 out of those 449 recordings were determined to be clean. Out of those 152 clean detected recordings, only 29 were false positives for AF by the linear SVM. Thus, with the noise artifact detection algorithm, we have been able to automatically discard poor quality noise corrupted signals thereby reducing the number of false positives from 156 to just 29. Moreover, our noise detection algorithm detected 97 recordings as corrupted. Based on our visual adjudication, in total 227 recordings were correctly detected while 22 were misclassified. Thus, the noise artifact detection accuracy is 227/ (152+97) = 91.16%, which indicates the efficacy of the proposed method. Note that our classification decision as to whether or not a given recording is clean or corrupted is based on the criterion that both two consecutive 30-second data segments have to be determined as either clean or corrupted using our algorithm. Hence, the remaining 200 recordings out of the 449 have had split classifications (e.g., one 30-sec was determined as clean and the other 30-sec noted as corrupted), thus, they were classified as indeterminate. The rationale for this criterion is to reduce false positive detection of AF.

V. Conclusion

The proposed time-frequency based noise artifact detection algorithm is shown to accurately detect corrupted PPG signals recorded by a smartphone camera. If the PPG signal is detected as clean, only then is it used for peak detection and AF identification, which should consequently reduce false alarms. Although this preliminary result is mainly focused on reducing false positives, once more AF data are available, we will explore noise detection and AF identification for a sufficiently large population. For future work, additional time domain-based waveform features can be combined with the VFCDM method to enhance the noise artifact detection process.

Acknowledgment

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