A Robust PPG Onset and Systolic Peak Detection Algorithm Based On Hilbert Transform

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***Abstract*— Recent advances in cardiovascular diseases (CVDs) have inspired the modern population to adopt different easy-to-use personal health monitoring devices that employ easy-to-acquire biosignal such as Photoplethysmogram (PPG) for regular and long-term monitoring of vital signs. However, the detection of clinically significant PPG fiducial points such as onset and the systolic peak is still an open area of research. In the present work, a robust and simple PPG onset and systolic peak detection algorithm is proposed based on the Hilbert Transform. The methodology uses signal derivative, Hilbert Transform, amplitude thresholding and slope-reversal based approaches. In contrast to other techniques, the proposed algorithm exhibits high efficiency with average sensitivity and positive predictivity of 99.83% and 100% respectively, as tested with PPG records collected from the MIMIC database, institutional laboratory and hospital respectively.**

Keywords—Amplitude thresholding, Hilbert Transform, Photoplethysmography, PPG onset; Slope reversal, Systolic peak.

I. INTRODUCTION

According to an alarming statistics of World Health Organization (WHO), 31% deaths around the world in 2016 are caused by cardiovascular diseases (CVDs). The fatal consequences of CVDs are still considered as the most critical healthcare issue [1]. Unfortunately, even to date, in most of the rural areas, different problems such as overpopulation, improper medical infrastructure, substandard transport services and the shortage of medical practitioner often imposes insurmountable barrier for the treatment of post cardiovascular complexities [2]. Consequently, different smart health monitoring devices are now become extremely popular which can be used as an effective alternative to reduce mortality rate and also to minimize expenses. A number of significant bio-signals can be easily recorded in these health monitoring devices and can be analyzed with high accuracy even in the absence of any medical practitioner. Most importantly, due to the ease of operation and the requirement of minimum infrastructural resources, these devices can be employed in remote rural area to carry out speedy diagnosis of critical conditions [3].

So far, multi-lead Electrocardiogram (ECG) signals have been popularly used by majority of the reported techniques because of its non-invasive nature and global acceptance in clinical domain [4]. Although, in recent days, Photoplethysmogram (PPG) signal emerges as an effective and non-invasive alternative of other standard bio-signals owing to its simple, convenient, low-priced acquisition technology and expert-free methodologies. Basically, PPG is an electro-optical method, which represents relative changes in the blood volume in different peripheral parts (such as fingertip, earlobe, and toe) of the body. The pulsatile ac part in the PPG signal morphology represents average changes in the blood volume. Whereas, the quasi-dc part is used to represent the effects of respiration and the influence of sympathetic nervous activity [5] respectively.

Numerous researches reveal the inherent potential of the Photoplethysmogram (PPG) signal for the assessment of different cardiovascular episodes and also for the evaluation of the blood circulatory system. Consequently, the applications of the PPG signal are not limited for the assessment of blood oxygen saturation [6] only. The features of the PPG signal are now being used to analyze different cardiovascular parameters such as heart rate [7], blood pressure [8] respectively. Moreover, PPG feature present suitable promise in the assessment of cardiac disorders such as premature ventricular contractions [9] also.

Temporal analysis of the PPG signal to determine different physiological parameters, such as pulse transit time (PTT) and heart rate requires accurate detection of onset and systolic peaks respectively. However, variant location and morphologies of pulse onset and systolic peaks due to different pathophysiological changes, such as aging, diabetic condition, atherosclerosis make its detection quite challenging for computerized health analysis systems [10].

So far, a number of computerized techniques have been proposed to carry out the detection of pulse onset and systolic peak points from the PPG signal [11-14]. In [11], the peak detection methodology utilizes an adaptive threshold-based technique on eighteen young and healthy subjects only. In [12] a method is proposed by generating blocks of interest-based on two moving average filters followed by a dynamic event duration threshold to identify only the systolic peaks in the PPG signals. The method of [12] is evaluated on forty healthy subjects. Shannon energy envelope estimator, Hilbert transform (HT) and moving average (MA) filter-based methods are used in [13] for the detection of systolic peaks and onset points in the pulse waveform using ten volunteers only. Variational mode decomposition (VMD) and center of gravity (COG) based techniques are adopted in [14], to carry out systolic peak detection only.

Majority of the above-mentioned research either uses (1) complicated methodologies [12-14] or uses (2) smaller

datasets with a limited pathological variety [11-13]. In the present research a robust and simple algorithm is proposed for automated and precise identification of PPG onset and systolic peak points, using Hilbert Transform based approach. The main contributions of this paper are: (i) Hilbert transform is used to enhance the PPG signal features and simple mathematical methods are used to determine PPG onset and systolic peaks respectively, (ii) based on the detected fiducial points, the algorithm is used to extract some time-plane features and finally, (iii) rigorous evaluation of detection efficiency of the algorithm is carried out over huge PPG records, as obtained from standard Physionet database as well as from normal volunteers and cardiovascular patients respectively.

II. Proposed Methodology

Different steps of the proposed methodology are presented in the following block diagram of Fig. 1.

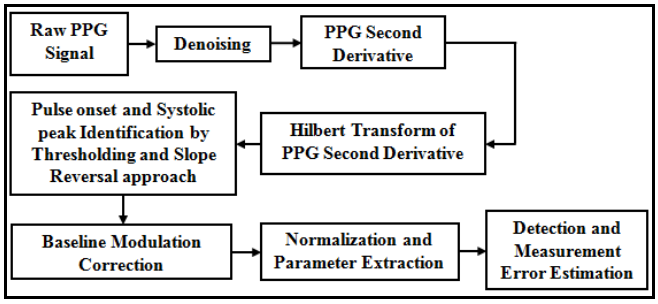

Fig. 1. Block diagram of the proposed algorithm

A. Preprocessing

Acquisition of the PPG signal is prone to different types of factors such as the amount of light incident on the photo-detector, variation of index finger pressure on the used PPG sensor, improper perfusion of blood at the marginal areas, and also the appearance of motion artifact related noises [15] respectively.

Since the proposed algorithm follows derivative-based methodologies, consequently it becomes noise sensitive. Hence, in the present work, a sixth-order Butterworth low-pass filter with 15 Hz cut-off frequency is used on all the PPG signal records under investigation to eliminate the unwanted high-frequency noise parts.

B. Detection of PPG onset and systolic peaks

Initially, after denoising of the PPG signals, the computation of first (FDPPG) and second derivative (SDPPG) are carried out by means of the equations as described below

$$FDPPG = \frac{d}{dt}(PPG) = \frac{d}{dt}[y(t) - y(t-1)] \quad (1)$$

$$SDPPG = \frac{d}{dt}(FDPPG) = \frac{d}{dt}[y(t) + y(t-2) - 2y(t-1)] \quad (2)$$

In the above equations, y(t-1) represents the current PPG sample, whereas, y(t-2) and y(t) are the preceding and the subsequent PPG samples respectively.

Now, Hilbert Transform is applied to the second derivative of the PPG signal. Initially, depending on the amplitude range, the whole Hilbert transformed data is subjected to a fixed threshold value as shown in Fig. 2 (a). After extensive evaluation over a number of PPG signal records, an amplitude threshold of 50% is empirically chosen to identify the higher amplitude regions. The chosen higher amplitude zones of the Hilbert transformed data are then used to identify the maximum peaks by searching for slope reversal points inside a window of fixed width as shown in Fig. 2 (b). Based on the location of the maximum peaks, left and right neighborhood samples of the Hilbert-transformed PPG data are examined to identify the primary and the next zero-crossing positions as depicted in Fig. 2(b). Then, on the basis of the location of each zero-crossing point, spotting of thirty samples is done on the actual denoised PPG data and an effective search zone is created as shown in Fig. 2(c) and 2(d). Now, among those spotted sample points on the PPG waveform and based on the location of the left zero-crossing point, only the sample with slope reversal characteristics is then spotted as the pulse onset. Likewise, using the location of the right zero-crossing point, only the sample with slope reversal characteristics is then spotted as the systolic peak and is shown in Fig. 2(e).

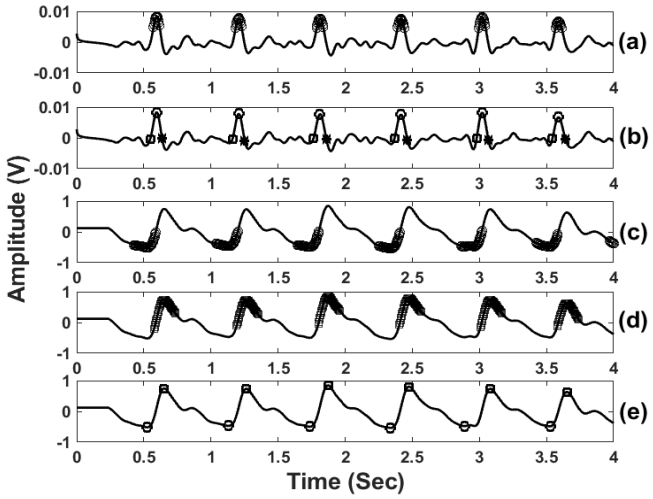

Fig. 2. (a) Amplitude values beyond a preset optimum value are spotted on the Hilbert-transformed PPG data (b) detected maximum peaks, left zero crossing points and right zero crossing points are indicated by circle, square and star symbol symbols respectively, (c) thirty samples are marked on the original PPG signal based on the left zero crossing point indices, (d) utilizing the location of the right zero-crossing point, thirty PPG samples are then spotted (e) after detection, circle symbols are used to mark the detected PPG onsets and square symbols are used to indicate the detected systolic peaks respectively.

Generally, the highest value of the human heart rate under maximum variation can be considered as 240 per minute [10]. The resultant lowest beat interval will be 0.25 seconds.

Hence, in the present research, the search window length is considered within 0.25 second for accurate detection of maximum peaks locations from the Hilbert transformed data.

C. Correction of baseline drift and normalization

Generally, in case of time-domain analysis of the PPG signal, majority of the parameters are extracted with regard to a common axis level. Therefore, unusual variation of the PPG signal baseline might often causes incorrect interpretation of the feature values.

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Although, sometimes owing to uneven breathing, abnormal movements of different body parts and shaky fingertip contact during recording, PPG signal baseline often presents unusual variation. The effect of such baseline variation can be noticed inside one PPG beat length as well as shown in Fig. 3(a). The effect of baseline modulation is removed by considering the first PPG onset point of a single cardiac beat as the starting point and is shown in Fig. 3(a).

After that, starting from the first to the next onset point, each PPG samples are then adjusted following an empirical formula and is elaborated in [10]. Immediate after the removal of uneven baseline wandering, the PPG signal data is then amplitude normalized from 0 to 1 by means of equation 3.

$$V_{norm} = \left(\frac{V_{signal} - V_{signal(min)}}{V_{signal(max)} - V_{signal(min)}} \right) \quad (3)$$

In the above equation, V_{signal} represents the PPG data after baseline correction; $V_{signal\,(min)}$ [or $V_{signal\,(max)}$] represents the minimum (or maximum) value of the PPG signal after baseline correction; V_{norm} represents the normalized PPG data.

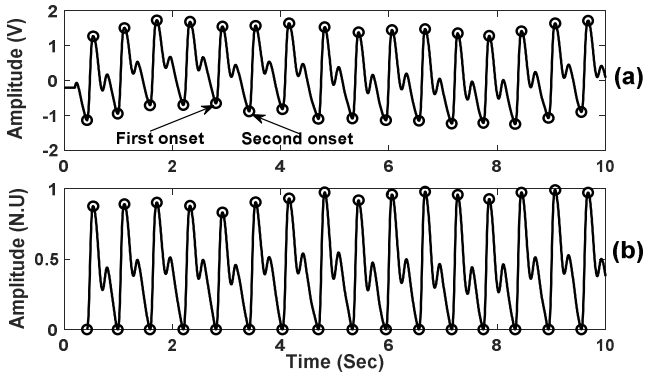

Fig. 3. (a) PPG signal record prior to the correction of baseline wandering and normalization, (b) the similar PPG record after correction of baseline wandering and normalization.

D. Feature extraction

Changes in PPG signal morphology could be regarded as an effective way out for non-invasive estimation and analysis of different physiological parameters and abnormalities. In the proposed research, fifteen time-plane parameters are extracted based on the location of pulse onset and systolic peak points of the PPG signal. However, for demonstration purpose, only single amplitude and a single duration parameter is chosen. Furthermore, it has been seen from visual inspection that the position and amplitude of different characteristics points in consecutive PPG beats, taken from the same record are often found to differ widely. The resultant inconsistency is reported in the present research in terms of detection and measurement error. The absolute value of the amplitude measurement error is computed as the percentage of average differences of each calculated characteristic point amplitude with the earlier, the absolute duration measurement error is computed as the percentage of average differences of each calculated characteristic point duration with the earlier.

In the present research, the reported amplitude and duration parameters are computed as follows;

Amplitude parameter = the difference of voltage from the fiducial point to the X-axis in normalized unit (N.U) and Duration parameter = difference of time between the detected fiducial point and pulse onset point in seconds.

III. RESULTS AND DISCUSSION

Evaluation of the developed algorithm was carried out using a huge number of PPG signal records (17,442 PPG beats) collected from the standard (1) MIMIC Database, which includes PPG data records from 96 ICU patients, (2) laboratory-acquired PPG signal data from 72 healthy volunteers via BIOPAC MP 45 (sampled at 250 Hz) and (3) also from 44 cardiovascular patients, admitted in the cardiology ward of Medical College and Hospital, Kolkata. During the process, informed consent form was taken from each participant following institutional policy and international protocol.

As a whole, efficiency of the proposed methodology is justified in terms of three different statistical parameters which are defined below –

$$Sensitivity\,(SE) = \frac{TP}{TP+FN} \times 100\% \quad (4)$$

$$Positive\ predictivity\,(PP) = \frac{TP}{TP+FP} \times 100\% \quad (5)$$

$$False\ discovery\ rate\,(FDR) = \frac{FP}{TP+FP} \times 100\% \quad (6)$$

True positive (TP) represents the number of fiducial points that are precisely detected, false negative (FN) represents the number of incorrectly detected fiducial points, FP represents the number of fiducial points that are detected by mistake.

So far, no online, annotated and standard PPG database is available and hence in this research only visual inspection is applied to validate all the detected onset and systolic peak points. The whole validation process is supervised by the institutional research scholars and the skilled medical persons from the Department of cardiology, Medical College and Hospital, Kolkata. After evaluation over the entire collected dataset, the proposed technique presents an average Sensitivity [99.98% (systolic peak), 98.68% (onset] and Positive Predictivity [100% (systolic peak), 100% (onset)] respectively, as listed in Table 1.

TABLE I. DETECTION EFFICINECY OF THE ALGORITHM

Record No	Heart rate	Systolic peak			Onset		
		Se (%)	PP (%)	FDR (%)	Se (%)	PP (%)	FDR (%)
MIMIC Data							
222b	67	98.41	100	00	100	100	00
25300030	71	100	100	00	100	100	00
Laboratory acquired normal Data							
1	78	100	100	00	100	100	00
33	70	100	100	00	100	100	00
Hospital acquired cardiovascular patient Data							
34	96	100	100	00	100	100	00
18	112	100	100	00	97.37	100	00
Average performance of all data							
Total		99.98	100	00	99.68	100	00

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The extracted amplitude feature in normalized unit (N.U) and time feature in second by the proposed algorithm are summarized in Table II. The overall average absolute amplitude and duration detection errors related to those extracted features are also summarized in Table III and are found to be within the permissible limits.

TABLE II. EXTRACTED HEIGHT AND DURATION FEATURES

Record No.	Avg. amplitude of the systolic peak (N.U)	Avg. systolic peak to onset duration (Sec)
MIMIC Data		
222b	0.86	0.21
25300030	0.82	0.32
Laboratory acquired normal Data		
1	0.87	0.20
33	0.81	0.13
Hospital acquired cardiovascular patient Data		
34	0.79	0.13
18	0.83	0.17
Average of all data		
Total	0.866	0.234

TABLE III. PERCENTAGE OF MEASUREMENT ERRORS IN HEIGHT AND DURATION

Record No.	Systolic peak amplitude (%)	Systolic peak to onset duration (%)
MIMIC Data		
222b	4.141	1.667
25300030	2.649	4.218
Laboratory acquired normal Data		
1	2.150	5.179
33	2.603	0.406
Hospital acquired cardiovascular patient Data		
34	3.841	2.283
18	6.592	3.712
Average of all data		
Total	4.455	3.813

Efficiency of the proposed algorithm has not been realized in any hardware platform. Whereas, in the present research, examination of the algorithm is carried out only in the MATLAB platform using a Windows 7 powered personal computer, equipped with Pentium core i3 CPU and a 4 GB RAM respectively. Moreover, on average the algorithm takes around 3 seconds to detect all the characteristic points and extract the features from a single PPG record of 1-minute duration sampled at 250 Hz,. This approximate time estimation suggests that the algorithm can be used for intermittent online applications as well.

PPG signal is highly sensitive to motion artifact and in this research, the adopted Hilbert transform is applied on the second derivative of the PPG signal. Hence, it is acknowledged that, in real life automated analysis, a superior denoising technique is required to remove the effects of motion artifact from the PPG signal record. Furthermore, it is evident from Fig. 3 that the algorithm successfully rectifies the baseline drift of the initial PPG cycle, if the primary PPG sample belongs to the onset point only. A similar case occurs for the last PPG cycle as well.

Based on the available literature, a reasonable comparison is presented in Table IV. The comparison table reveals that in terms of the number of beats and pathophysiological variety, the proposed algorithm outperforms other methods. However, dissimilarities in the adopted databases, the total number of used PPG beats and differences in the type of validation process mentioned in the literature also imposes serious limitations for accurate assessment.

TABLE IV. COMPARISON OF THE PROPOSED METHOD WITH RELEVANT STUDIES

Systolic peak			
Ref.	**Beats**	**Se (%)**	**PP (%)**
Adaptive threshold [11]	22,623	98.04	100
Event related moving averages [12]	5,071	99.89	99.84
Hilbert transform [13]	2,286	100	100
VMD and COG [14]	86,996	99.10	99.77
	16,213	99.39	99.67
Proposed	17,442	99.98	100
Onset			
Ref.	**Beats**	**Se (%)**	**PP (%)**
Adaptive threshold [11]	22,623	98.84	99.98
Hilbert transform [13]	2,286	100	100
Proposed	17,442	99.68	100

Different PPG waves taken from different databases along with identified systolic peak and onset points by the proposed algorithm are shown in Fig. 4.

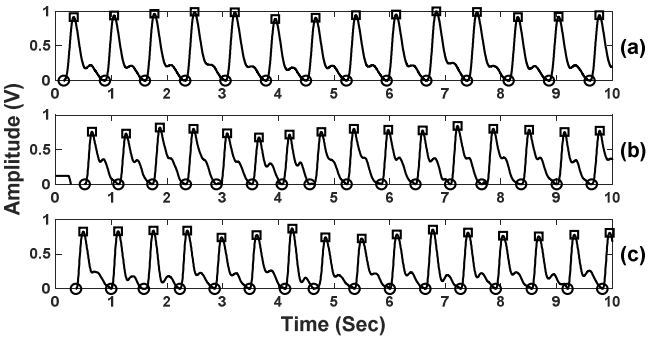

Fig. 4. PPG signals with the detected onset and systolic peak points from a (a) MIMIC data, (b) Normal data and (c) a cardiovascular patient data.

IV. CONCLUSION

In the present research, a robust and simple onset and systolic peak detection algorithm is proposed via Hilbert Transform. To the best our knowledge, no such Hilbert Transform based algorithm is proposed to date, which is simple enough to extract these fiducial points from the PPG records with a wide pathophysiological variation.

Apart from the Hilbert Transformation, the adopted derivative-based method and other computationally simple methodologies for instance; amplitude thresholding, detection of slope reversal points and use of an empirical formula based methods guarantees trouble-free realization of the algorithm on a hardware platform.

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The result indicates that the algorithm presents high efficiency with an average Sensitivity, and Positive predictivity of 99.83% and 100% respectively, while evaluated over 17,442 PPG beats with wide pathophysiological varieties. However, in the future, the proposed algorithm will be further extended to make it useful for PPG based health analysis applications.

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