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A Novel Algorithm for MA Reduction in PPG Signals for Accurate HR Monitoring

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Abstract*: Heart rate is measured as the number of beats per unit of time and is expressed in beats per minute (bpm). For the extraction of this important physiological indicator, photoplethysmography (PPG) is widely adopted by the medical professionals since the existing methods lack accurate measurement and cause some uncomfortableness to the subject due to motion artifacts (MA). A bout of innovations and experimentations resulted in a number of algorithms and methods that suppressed the effect of MAs. A novel algorithm that exploits the method of both Empirical Mode Decomposition (EMD) and Empirical Wavelet Transform (EWT) is tackled in this paper.

***Keywords*: Heart Rate, Motion Artifacts, Photoplethysmography, Empirical Mode Decomposition, Empirical Wavelet Transform**

I. INTRODUCTION

Heart rate is one of the most important physiological indicators that can reveal a lot about a person's fitness and any change or variation in this parameter can giveaway information about their stress levels, sleep quality, exercising load or life style. And moreover can indicate different abnormal conditions that may result in various diseases. ECG, the existing method of HR estimation, measures the spikes of the electrical signals generated in the heart that control the expansion and contraction of heart chambers. But such methods make uncomfortable for the user because it uses some sensors which are attached to the chest or bare body for a long period of time. It also restricts the movements of the subject while measuring the HR. So these are not viable methods for continuous measurement and when unconstrained movement is required. Thus the photoplethysmography (PPG) method becomes much more convenient solution since it uses some sensors that are embedded in a wrist band or watch type modules and are attached to the peripheral parts of the body like wrist, earlobes or fingertips.

PPG is an optical measurement method that measures the changes in the volume of blood as it distends the arteries and arterioles in the subcutaneous tissue. Theses blood volume changes are synchronous with the cardiac rhythm and hence HR can be easily measured. The PPG waveform therefore comprises a pulsatile ('AC') physiological waveform attributed to cardiac synchronous changes in the blood volume with each heart beat, and is superimposed on a slowly varying ('DC') baseline with various lower frequency components attributed to respiration, sympathetic nervous system activity and thermoregulation [1].

The PPG sensor unit comprises of a LED which emits light to the skin and a photo detector which measures the light intensity variations that is reflected or transmitted through the skin. But the motion artifacts caused by body movements or sensor deformation makes the PPG based HR estimation more challenging. It would results inaccurate measurements unless the system cancelled out the effects of MAs with the application of a set of compensation algorithms. The past decades have witnessed grand progress in the development of different methods and algorithms that are used to suppress the effect of MAs. A three-stage TROIKA method [2], JOSS method [3], adaptive filtering [4], independent component analysis [5], empirical mode decomposition [6], spectral subtraction [7] and Kalman filtering [8] are some of the methods that are proposed to remove or attenuate the effects of MAs. Many of these HR estimation algorithms are tested on a publically available dataset made by the IEEE Signal Processing Cup 2015 and reported that the improvements in performance are accompanied with either increased number of free parameters or with high execution time.

This paper details a novel algorithm for HR estimation that is based on a combined method of Empirical Mode Decomposition and Empirical Wavelet Transform. The noise signature is estimated and removed with the help of EMD and calculated the instantaneous frequency using EWT from which we can estimate the heart rate very accurately. In contrast to the already existing algorithms, the proposed solution gives much more convenient measurements.

II. HR ESTIMATION ALGORITHM

The flow chart of the proposed solution is shown in Fig. 1, which consist of 5 main blocks- pre-processing and de-noising, frequency domain analysis, frequency portioning, analytic function and HR estimation. Pre-processing and de-noising is done with the help of Empirical Mode Decomposition for the removal of noise to recover a reliable signal. And among these second and third blocks are coming under Empirical Wavelet Transform, where the instantaneous frequencies are determined.

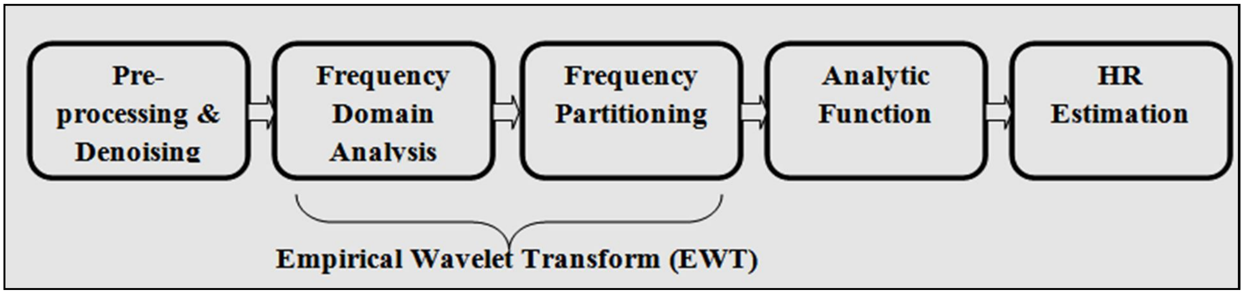

Fig. 1 Flow chart of the proposed HR estimation system

A. Pre-processing and De-noising

The effect of MAs during the data collection process is particularly significant during a stress test. High frequency noise caused by the sensor deformation and baseline wandering caused by the respiration of the subject are the main sources for these MAs. Our aim is to separate the true PPG signal from the undesired artifact signals.

EMD, proposed by Huang, serves as a good tool for artifact reduction especially in nonlinear signals such as biomedical signals. It adaptively decomposes a signal into a sum of Intrinsic Mode Functions (IMFs).

Given a signal X(t). All the local maxima in the X(t) are connected by a upper envelope $E_u(t)$ and all the local minima are connected by a lower envelope $E_l(t)$. Then by sifting process, used to extract IMFs, the first IMF is obtained as,

$$H_1(t) = X(t) - m_1(t) \quad (1)$$

Where $m_1(t)$ is the mean of two envelopes.

Sifting process is repetitively applied on the $H_1(t)$, until it satisfies the IMF condition, to obtain $h_1(t)$. Then we can write,

$$R_1(t) = X(t) - h_1(t) \quad (2)$$

Where $R_1(t)$ is the residue that contain some useful information even after the last sifting process. Now apply the sifting process to $R_1(t)$ by considering it as a new signal.

$$R_1(t) - h_2(t) = R_2(t)$$
$$R_{N-1}(t) - h_N(t) = R_N(t) \quad (3)$$

Stop this procedure when the $R_N(t)$ becomes a constant or a monotonic slope. From equations (2) and (3) we get,

$$X(t) = \sum_{n=1}^{N} h_n(t) + R_N(t) \quad (4)$$

Thus EMD decomposes the signal X(t) into N IMFs and a residue signal. Now apply the following algorithm to the obtained set of IMFs.

Algorithm for EMD

1) Sum the first IMFs whose oscillatory pattern is similar to those in the QRS complex.
2) Identify the zero crossing points on LHS of left minimum and on RHS of right minimum of the fiducial points (R wave), which forms the boundary of the complex.
3) Do proper windowing to keep the QRS complex.
4) Determine the number of IMFs that contribute to the noise by some statistical tests.
5) Find the noise order and use partial reconstruction for filtering.

B. Empirical Wavelet Transform

After de-noising, the processed signal can be separated into a number of modes known as AM-FM components having a compactly supported Fourier spectrum. Segmentation of these different modes which is equivalent to the segmentation of the Fourier spectrum provides adaptability. By taking the Fourier transform of the signal we can obtain the spectrum of the signal. Let N be the number of segments to which the spectrum is to be divided. Total limit of the spectrum is in between 0 and π and limit of each segment is ω_n. In order to divide the spectrum into N segments, a total of N+ 1 boundary are needed. To find such boundaries, first detect all the local maxima in the spectrum and rearrange them in decreasing order. Assume that the algorithm found M maxima, two cases can appear; [9]

1) $M \geq N$: The algorithm found enough maxima to define the required number of segments, and then we keep only the first N-1 maxima.

2) M<N: The signal has less modes than expected, then we keep all the detected maxima and reset N to appropriate value. With this set of maxima plus 0 and π we define the boundaries ω_n of each segment. This is the centre between two consecutive maxima. (ω_0=0 and ω_n=π).

Now multiplying these mid points with an appropriate window function, we can divide the whole spectrum into different modes and the corresponding AM-FM components are obtained by taking the inverse transform of each segment.

C. Analytic function and HR Estimation

The representation in the time-frequency domain is useful to have the knowledge of all the components summarized in a single segment. The AM-FM signals can be represented as

$$f(t) = F(t)\cos\varphi(t) \tag{5}$$

Using the Hilbert transform, can derive the analytical form f_a of the above function as

$$f_a(t) = f(t) + iH_f(t) \tag{6}$$

where $H_f(t) = \frac{1}{\pi} p.v. \int_{-\infty}^{+\infty} \frac{f(t)}{t-\tau} d\tau$, is the basic definition of the Hilbert transform of a function.

Thus, $$f_a(t) = F(t)e^{i\varphi(t)} \tag{7}$$

From this analytical form we can extract the instantaneous frequency and instantaneous amplitude. So after applying Hilbert transform to each of the extracted AM-FM components, we can have the instantaneous frequency and thus corresponding HR can be estimated.

III.DATABASE AND METRICS

A. Database

The data sets used here were provided by the IEEE Signal Processing Cup 2015. It is given in Table I. The dataset consist of 23 recordings which were collected from different subjects (18 -58 years old) performing different physical exercises. The dataset consist of PPG, three-axis accelerometer and ECG signals. The PPG signals were recorded using two PPG sensors whereas the acceleration signals were recorded using a 3-axis accelerometer along with the ECG signal recorded simultaneously from the chest using ECG electrodes. PPG sensors make use of green LEDs having a wavelength of 515 nm. All the above signals were sampled at rate of 125 Hz.

The subjects had performed three types of activities. T1 involved walking or running on a treadmill, T2 involved different rehabilitation arm exercises and T3 involved of intensive forearm and upper arm movements. The ECG signals were considered as the ground truth HR in BPM.

TABLE I DATABASE FROM IEEE SP CUP 2015

REC	SUBJECT ID	ACTIVITY TYPE	AGE / WEIGHT / HEIGHT	SEX	HEALTHY?
1	1	T1	18-35y /- /-	M	Y
2	2	T1	18-35y /- /-	M	Y
3	3	T1	18-35y /- /-	M	Y
4	4	T1	18-35y /- /-	M	Y
5	5	T1	18-35y /- /-	M	Y
6	6	T1	18-35y /- /-	M	Y
7	7	T1	18-35y /- /-	M	Y
8	8	T1	18-35y /- /-	M	Y
9	9	T1	18-35y /- /-	M	Y
10	10	T1	18-35y /- /-	M	Y
11	11	T1	18-35y /- /-	M	Y
12	12	T1	18-35y /- /-	M	Y
13	13	T2	20y/64kg/162cm	M	Y
14	14	T2	29y/70kg/169cm	M	Y
15	15	T2	21y/77kg/188cm	M	Y
16	15	T3	21y/77kg/188cm	M	Y
17	16	T3	19y/54kg/174cm	M	Y

18	13	T3	20y/64kg/162cm	M	Y
19	17	T3	20y/57kg/174cm	M	Y
20	18	T2	19y/70kg/180cm	M	Y
21	18	T3	19y/70kg/180cm	M	Y
22	19	T3	21y/73kg/180cm	M	Y
23	20	T2	58y/70kg/156cm	F	N

B. Metrics

The Absolute Error (AE) or mean error is used as the measure of accuracy of each HR estimate:

$$AE_i = | F_{est}(i) - F_{true}(i) | \qquad (8)$$

Where F_{est} (i) and F_{true} (i) are the estimated and the true HR value in the i^{th} time window in BPM.

IV. RESULTS

The program is executed for each data set of observed signal and true signal, and obtained the mean error. The performance of the proposed heart rate estimation algorithm is detailed in Table II.

The mean error of all the 8 set obtained is, Mean Error = 0.37 BPM.

Table Ii Performance Evaluation Table

OBSERVED SIGNAL	TRUE SIGNAL	MEAN ERROR
D01	S01	0.0012
D02	S02	0.4984
D03	S03	0.5409
D04	S04	0.6162
D05	S05	0.5057
D06	S06	0.4194
D07	S07	0.3592
D08	S08	0.0720

An example of the true and observed HR for the first recording, with which the best performance is achieved, is shown in Fig. 2.

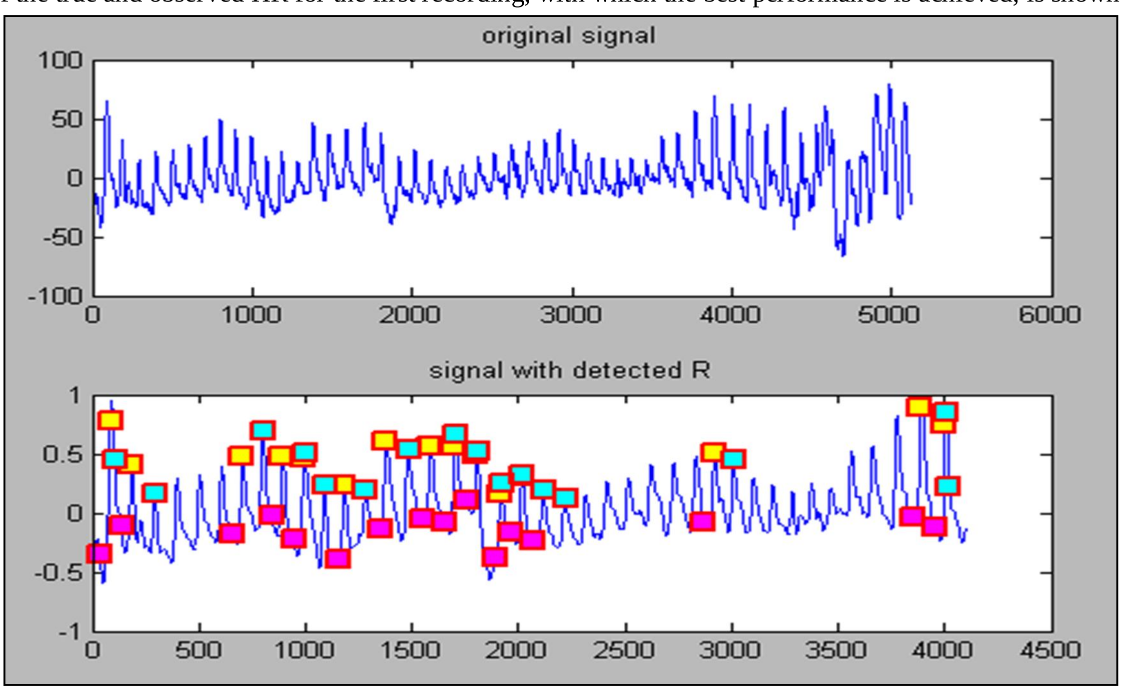

Fig. 1 The true and estimated Heart Rate for first recording

The performance of alternative HR estimation algorithms tested on the same dataset or a part of it, is provided in Table III. Evaluating on the same recording that used in the previous algorithms, the proposed system results in a mean error of 0.37BPM. the method presented in this study takes under 10s to process the complete PPG dataset whereas TROIKA takes several hours, JOSS takes 300s, WFPV methods takes 10s or above. Thus the developed algorithm outperforms all other methods.

Table Iii Comparison Of Different Hr Estimation Algorithms

ALGORITHM	MEAN ERROR	EXECUTION TIME
TROIKA	2.34	Several Hours
JOSS	1.28	300s
WFPV	1.05	Above 10s
WFPV+VD	0.65	10s
PROPOSED ALGORITHM	0.37	Below 10s

V. CONCLUSIONS

The proposed algorithm, based on the Empirical Mode Decomposition (EMD) and Empirical Wavelet Transform (EWT), provides an alternative way for tackling the motion artifact dilemma and can serve as a baseline performance for further studies. The algorithm has low computational cost and is well suited for fitness tracking and health monitoring in wearable devices. The mean error is significantly reduced and thus reduced the effect of motion artifacts.

PPG has been widely utilized in clinical community and medical field, and proven its ability not only in real time monitoring physiological parameters, such as blood oxygen saturation (SaO2), heart rate (HR), blood pressure (BP), respiration, and cardiac output (CO), but also in vascular assessment (arterial disease, arterial stiffness and aging, endothelial function, and vasospastic conditions) and autonomic function assessment (HRV, blood pressure, orthostatic intolerance, thermoregulation). Future research may concentrate on the usage of other spectral estimation methods and advanced de-noising methods such as Ensemble Empirical Mode Decomposition (EEMD) to get a much more reliable signal.

The development of a ring sensor, which would require fewer degrees of freedom due to its insusceptibility to motion in two axes, would be a useful step for future research.

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