Research Article

Survey on Methods of Obtaining Biomedical Parameters from PPG Signal

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Abstract. In today's world effective monitoring of biomedical parameters are essential. There are several applications that use these parameters to analyze the health conditions of an individual. PPG signal is one of the vital biomedical parameters which can be obtained by non-invasive method. Extracting necessary details from this signal is a crucial task. PPG signal contains various information such as rate at which heart beats, respiration rate, blood pressure, etc. Effective methods required to get necessary details from a raw PPG signal. Let us study various algorithms that are used to extract these features, along with its pros and cons.

Keywords: Photo Plethysmograph - PPG, heart rate, respiration rate, blood pressure, pulse wave velocity, Wavelet.

1 Introduction

Biomedical signals such as EEG, ECG, EMG, PPG carry vital information about the activity of human organs, by extracting details from these signalshealthconditionof the organs can be monitored. Various studies are going on about the information contained by these signals. Among these signals Photo Plethysmography draws more attention from the researchers[19]. PPG measuring devices are used in various equipment to find the biological signal. PPG can be obtained through various methods. PPG signal can be extracted from human beings through two methods contact and non-contact. In contact method an infrared light is made to pass through the veins at locations in a body like a wrist, finger and earlobes then the light is collected by the suitable detector, change in blood volume gets reflected in the change in absorption rate of light. The signal obtained carries information of heart activities [5-6]. Different light sources can be used to get different results. Major issues in this method are motion artifact, the pressure used to hold the wearable device in position and source of light [6-8]. The contact method may follow the reflective mode of operation or transmissive mode. In a reflective mode both light emitter and receiver reside side by side on the location under monitoring [12-13].

In transmissive mode source will be on one side and the detector will be on the other side whereas the monitoring area is between source and detector [13]. In a non-contact method, a camera is used to capture the subject whose PPG signal must be\obtained from these images, a PPG signal is extracted. Ambient light or different light sources can be used to illuminate the subject for better results. Several pieces of research are going on under IPPG, Imaging Photo Plethysmograph monitor PPG signal and this method overcomes various issues faced in the contact method [9-11]. The camera used in IPPG may be of a digital camera, infrared camera, or a mobile camera. The PPG signal obtained from a low-cost noninvasive technology contains information on the blood volume change in the tissues that are due to the cardiovascular system. Hertzman was the one who termed Photo Plethysmograph [15]. PPG signal comprises of AC as well as some DC component; AC is due toblood volume change that reflects much of cardiovascular activity and DC is due to thermoregulation, respiration, sympathetic nervous system activities and Venous flow [5]. Several classic methods such as Poincare, power spectral analysis, time-delay analysis, exponent and surrogating have been proposed to determine the characteristics of PPG and from its results that are used for various medical applications [16-18]. This paper will concentrate on the methods used to extract features from the PPG signal that may be obtained fromanyoftheabovetechniques.

2 Methods for Extracting Information from PPG

Extracting features from the PPG signal started earlier in 2000 and still, the researchers are going on to enhance the methods. The PPG signal holds all the vital information about the cardiovascular system by analyzing its variousheart- related issues that can be identified at the earliest and can be treated. Tradition methods as well has latest methods have several similarities and dissimilarities which in detail will be portrayed in forth comingsections.

2.1 Wavelet analysis of PPG Signal

Wavelet transformation is an analysis where frequency and time are simultaneously observed. It can be used to analyze signals that are not steady such as biomedical signals. Continuous wavelet transform is used here to broadly analyze frequency components.
Morlet wavelet is exploited to obtain more details. The tidal wave is shown in the figure. 1 which indicates the blood vessels hardening. TWv, the voltage difference of percussion waves Incisors and TWt, time difference of Percussion wave Incisors is used to form stress indexusing wavelet analysis on PTG [19]. Refer figure 2 for Morlet waveform.

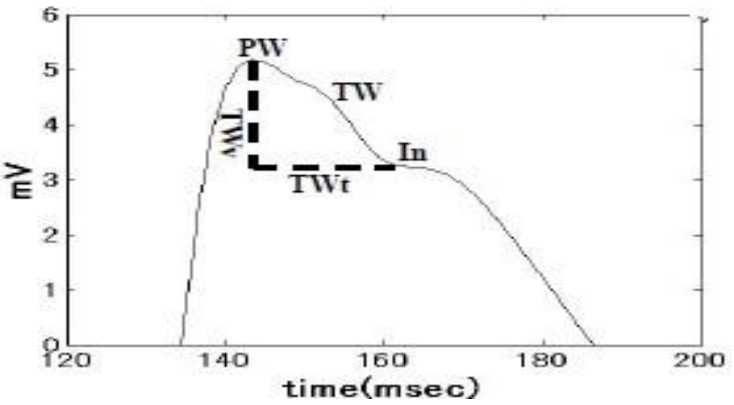

Fig. 1. PTG waveform showing Tidal wave region indicating TWv and TWt.

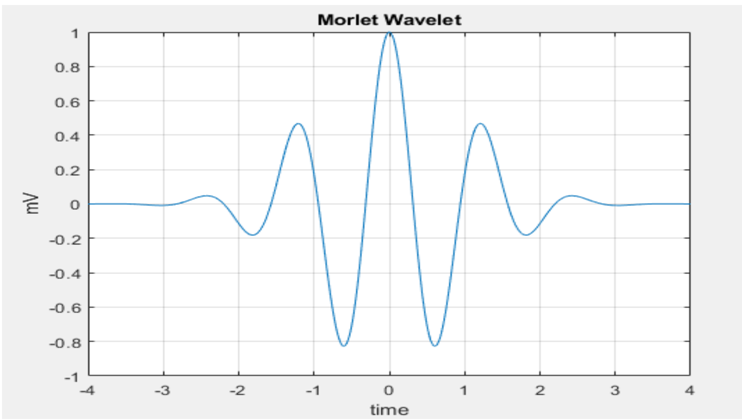

Fig. 2. Morlet Wavelet simulated using MATLAB.

In Resting stage PTG is measured where no noise source is used and in stress stage PTG is measured with increased exposure to noise source, the difference in stress index is observed for these two stages and considerable change is noted.

2.2 PCA on PPG

Principle Component Analysis invented by Karl Pearson to change set of variables that are correlatedintosetofvalues that are not correlated which involves orthogonalchanges [20]. Various features such as pulse to pulse interval, pulse amplitude, upslope, downslope, area of pulse and Wavelet decomposed band are used to determine relative respiratory effortsignal.Thedesiredfrequencyfrom0.15to0.45Hz is selected as it is the respiratory frequency range. Orthogonal property is used to remove redundant information [21].

$$Relative\ Effort\ (PPtt) = 0.41 * Area + 0.0001 * Upslope + 0.06 * Peakamp + 0.84 * PWA - 0.11 * PPInterval - 0.04 Valleyamp - 0.0002 * Downslope - 0.21 Wv \quad (1)$$

Features having weight less than 0.1 are rejected and those having more than 0.1 such as PWA, PPInterval, Area andWv features are selected to estimate relative respiratory effort. Peakamp decreases as tissue blood volume increases and vice versa. During Systole PWA is directly proportional to blood volume and PPInterval represents period of Heart cycle [22- 23].

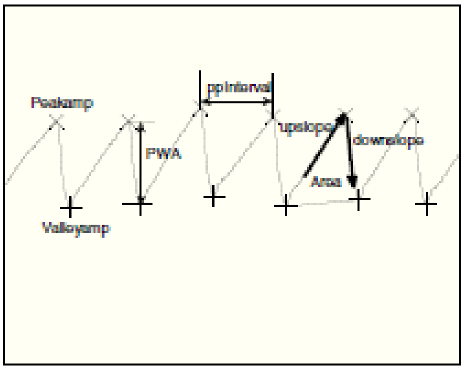

Fig. 3. PPG Signal showing peakamp, ppinterval, upslope, downslope and valleyamp.

2.3 Bilateral Photo plethysmography analysis with fractional order Feature

PPG measurement detects blood volume change inearlobes, fingers, and wrist unilaterally as well as bilaterally. Bilateral measurements increase as vascular disease evolve. [24]. The bilateral measurement is taken by measuring two PPG signal one from left hand thumb and other from right hand thumb, synchronously. The Sprott System is used to design a Self- Synchronized Error Function. The output of master is $\varphi 1$ and output of slave is $\varphi 2$. Data acquisition controller along with a Computerized Assistance System is used to collect data from PPG Signal and Screen the stenosis level in patient. Norm of $\varphi 1$ and $\varphi 2$ are calculated which gives the fractional order dynamic error, ψ. As the fractional order dynamic error increases degree of stenosis also observed to show considerable increase [25]. Refer figure 4 for relationship between degree of stenosis and fractional-order dynamic error.

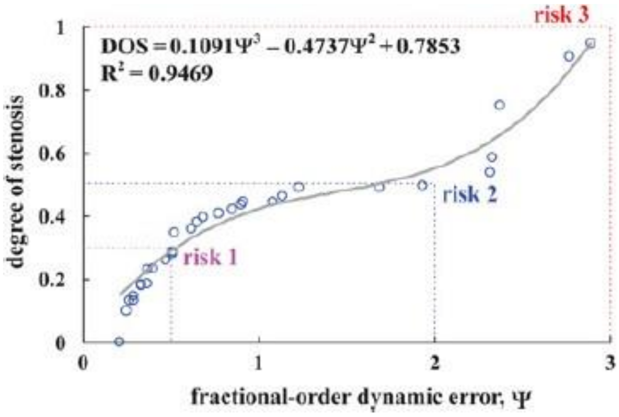

Fig. 4. Degree of Stenosis vs Fractional –order dynamic error.

2.4 PWV and PTT

In traditional way of measuring Pulse Wave Velocity (PWV)PPG signal along with ECG is measured, here in order to measure pulse transit time (PTT) two PPG measurements alone are considered. PTT is the duration from systolic to diastolic peak. In PPG duration of two peaks from PPG waveforms measured in different locations of body will give PTT. PWV is inversely proportional toPTT [26]. One PPG measurement is taken from wrist and another taken from finger, the wave form is shown the figure5.

$$PTT = L/PWV \tag{2}$$

L is the length travelled by pulse.

$$PWV = \sqrt{Eh/R\rho} \tag{3}$$

E=Young'sElasticitymodulush=thicknessofvesselwall
ρ = function of blood density R = radius of blood vessel.

$$PTT = L\,(cP-c/4) \tag{4}$$

P = Blood pressure C = Propagation speed of wave

$$P = A + B\,(PTT) \tag{5}$$

BP and PTT are related linearly. As BP increases PTT decreases, hence they are inversely proportional. Constant terms A & B can be calculated from PearsonCorrelation method. Hence Diastolic and systolic Blood Pressure can be determined [27]. Positioning of PPG sensor is difficult at wrist compared to finger and depth of radial artery vary from person to person, intensity of sensor and pressure between skin and sensor, motion artifact are the issues that may cause distortions during PPG measurement[28].

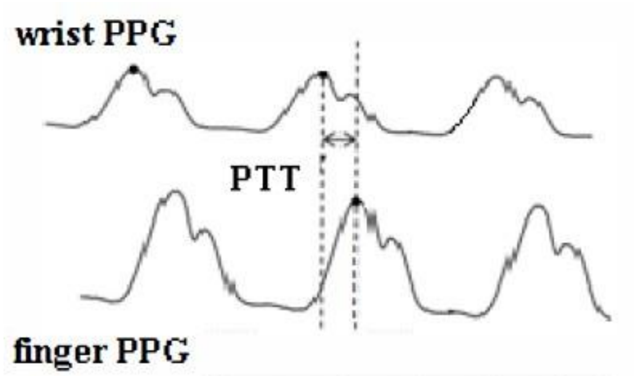

Fig. 5. PPG waveform measured from two different body locations.

2.5 Chaotic Character analysis Time delay Embedding and Lyapunov Exponent Methods

PPG characteristics is observed to have deterministic chaos. Dynamics in time series is reconstructed using Time delay embedding, this reconstructed trajectory holds vital time series characteristics which in turn reveals details of PPG signal properties [31]. To obtain independent coordinates, the time delay lag should be considerably large. Fourier analysis is used to obtain period of lag as quarter time period of predominant component. Minimal of 4 dimensions are needed to reconstruct the trajectory[17].
To identify the chaotic characteristics of a system quantitative and qualitative characterization of its dynamic behavior is essential, which is provided by Lyapunov exponent. At least one lyapunov exponent shall be positive for a chaotic system [31]. Using Wolf method lyapunov exponent can be determined for the time series. Limitations of determining Largest Lyapunov Exponent (LLE) is that even for non- chaotic system most methods may produce positive LLE [29]. Refer figure 6 for reconstructed trajectory using time delay embedding technique.

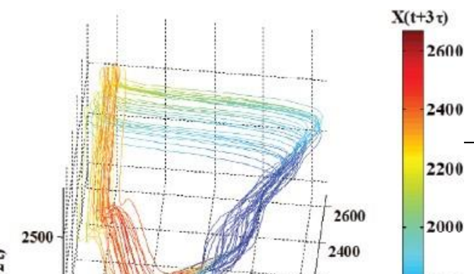

Fig. 6. Reconstructed trajectory by Time Delay Embedding.

2.6 Poincare Section

It determines chaos observed in phase space, hence it is a best tool in exploring dynamic characteristics of a system. As observed in the figure 7 the expansion, bending and stretching of trajectories along attractor tend to reveal the vital properties of the chaotic dynamics and dependencies on initial conditions [30]. Chaotic characteristics of PPG dynamics are determinism, predictability and dependency on initial condition. These features are useful to measure human physiological andmental conditions[31].

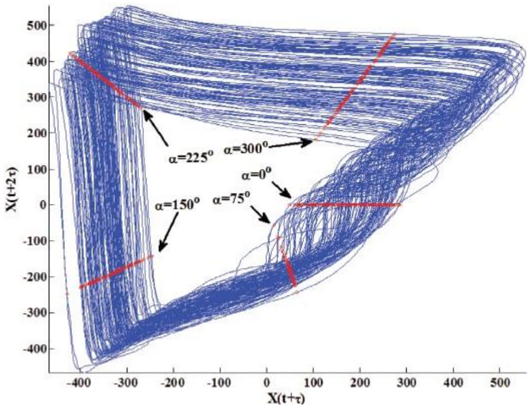

Fig. 7. Reconstructed trajectory using Poincare.

2.7 Poincare Section

DecompositionbasedonGaussianbasisrepresentationgives spatial and frequency variation of the PPG signal. By wave propagation theory the PPG wave is associated with progressive and regressive waves, hence all these waves are considered while modelling Gaussian function. PPG signal can be represented as several wave form sunder Gaussian basis decomposition as shown in figure 8.

$$P'(t) = \sum_{i=1}^{n} ai \times e^{-\left(\frac{t-bi}{ci}\right)^{2}} \qquad (6)$$

For n Gaussian basis 3n parameters are used to approximate PPG Signal. To get a better propinquity effect optimization is done and it removes squared error that is being introduced during approximation. Modified Gaussian–Newton method is used is used to find the unknown element L in optimized Gaussian Basis, first order derivative is considered [32]. It consumes less computation time. Finally, Hilberttrans- form is applied to the Gaussian Basis to extract frequencies and phases from which HR and RR measured. This method compares ECG and manual respiration monitoring, accuracy of 7 bpm was achieved [33].

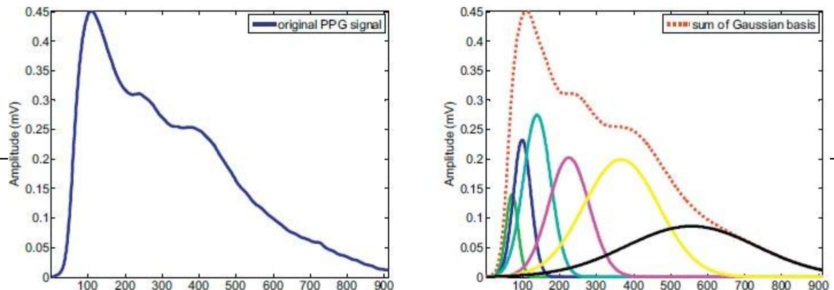

Fig. 8. (a) PPG Signal measured from finger. (b) Sum of Gaussian basis.

2.8 Asymmetric Least Square Spectrum Subtraction and Bayesian Decision Theory on PPG

Handling Motion artifacts while extracting features from PPG Signal is a great challenge. Various techniques are exploited to filter motion artifacts among them Adaptive Filtering [34]-[35]and Spectrum Subtraction [36] are popular and widely used. They have less complexity in computation but not robust and ineffective. Asymmetric Least SquareSpectrum Subtraction removes MA in an effective way compared to conventional Spectrum Subtraction method and alsoreduces undesiredpeaksinspectrumasthemethodusedisindependent of reference peaks. Bayesian decision method uses pattern recognition to identify spectral peaks of heart rate. The heart rate estimated in Bayesian method is again refined to give a better estimate by a post processing stage. Periodogram has been used to find the power spectrum of PPG Signal[37].

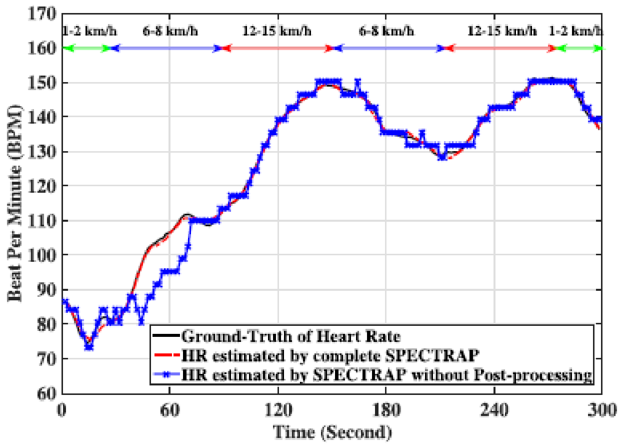

Fig. 9. Heart rate measured with and without post processing.

2.9 TROKIA

Heart rate monitoring is done using this method which was derived from the names spectral peak tracking, signal decomposition andsparse signal Reconstruction. First stage is decomposition which removes motion artifacts partially from raw PPG Signal. Singular Spectrum Analysis is exploited to perform signal decomposition as it isolate noise from desired oscillatory signal [38]. Second stage, Sparse signal reconstruction is done to improve the resolution of spectral estimation, good robustness and reduced variance which overcomes disadvantages of nonparametricspectrum estimation [39]. Sparse signal reconstruction needspreprocessing to obtain sparse spectra. SSR is performed by an algorithm called FOCUSS which is robust, it is used mostly to determine localization and direction of arrival Spectral peak tracking selects only the peaks that are associated with heart rate and reject that are not associated[40].

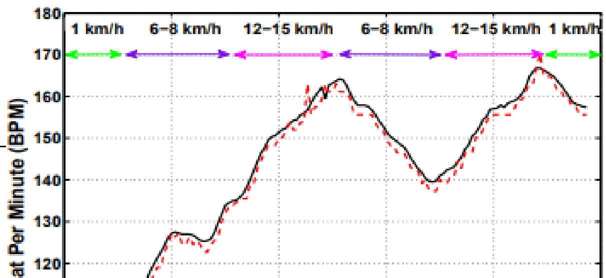

Fig. 10. Estimated heart rate by TROIKA method.

2.10 Joint Sparse Signal Recognition and Spectra Fusion

It is an extended method of Sparse Signal Reconstruction. It exploits the same M-FOCUSS obtain sparse spectra. L vectors are calculated by JSSRmethodandsparsespectra of PPG signal. Spectra Fusion is used to estimate respiration rate from obtained sparse spectra. Signal quality of the sparse spectra is analyzed and classified into three categories asgood, moderates and poor with the help of kurtosis; larger kurtosis means good quality spectra. For estimating respiration rate only good quality sparse spectra are considered, if suppose they are absent moderate quality is considered. Average of the considered spectra is taken and processed by RRT method to determine the Respiration rate, averaging of values can be done before or after implementingRRT [41].

3 Discussion

PPG signal has vital information about cardio vascular activityitisevidentfromallthestudiesthataremadeearlier and predict various biomedical parameters such as HR, BP, RR, BVC, PR and diagnosing of heart disease are also possible. Several algorithms are discussed to analyze PPG signal and extract various useful information from them. Research are still going on in analyzing PPG signal to understand it completely. Even latest methods fail to expose the complete possible feature that PPG holds withinit.

4 Conclusion

Best location to measure PPG signal are fingers but for various appliances this may not be suitable, so most of the equipment measure PPG from wrist which is convenient even when the person is performing exercise and in active motion. Motion artifact is a great challenge in extraction features without error, algorithms such as TROIKA, SPECTRAP and Sparse Spectral analysis were able handle these artifacts. By employing post processing techniques such as RRT, Spectra fusion, pattern classification method such as Bayesian decision and Spectral Peak detection estimation accuracy can be improved which also handles improper placing of sensor over the skin. Machine learning techniques such as k-means classification and decision tree are being used in every field for better enhancement and it finds more suitable position in Biomedical signal processing as well, as a future enhancement technique.

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