Heart Rate Variability(HRV) Analysis: A Comprehensive Review

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Abstract - *Heart Rate Variability (HRV) analysis a comprehensive review Abstract HRV is an indirect indicator of functioning of Autonomic nervous system(ANS). Many diseases can be identified at an early stage and their prognosis can be monitored by analysing HRV. The common diseases correlated with HRV are Myocardial-Infarction, Hypertension, Arrhythmias and Diabetes. HRV contains voluminous data and require much time to analyse. If it is interpreted into numerical values, which is easy to understand. The literature review goes in detail about the different techniques and various bio- signals used to analyse HRV. The signals used are Electrocardiogram(ECG), Photoplethysmography(PPG) and Ballistocardiogram(BCG) signals. Among ECG signals analysis, common technique used for QRS detection is Pan and Thompkins. How-ever much more accuracy and removal of ripples was achieved by Hamilton technique by using search back threshold values. The Phasor transform algorithm is the latest technique which converts HRV data into complex numbers. The advantage of this technique is easy to compute, require less data storage and its robustness. BCG is another non-invasive technique, produces graphical representation of vibrations produced by pumping action of heart, by placing sensors at bed or chairs it can be recorded. But it has difficulty in detecting individual heart beats. Among ECG, PPG and BCG signals, ECG is the standard technique. PPG analysis gives 98.8% accuracy by adopting different motion artefact removal techniques and algorithms. PPG signals analysis has attracted the researchers as it can be recorded easily at the fingertip. Most of the soft wares are available for HRV analysis. Among them KUBIOS software is found to be best and reliable. The latest version is 3.2.The review gives an insight of the usefulness, applications of various techniques used to extract HRV parameters by different soft wares and algorithms. It also suggests the physiological signals to extract HRV.*

Keywords:*AutonomicNervousSystem(ANS),Electrocardiogram(ECG),Photopletysmography(PPG),Ballistocardiography(BCG),Heart rate variability(HRV)*

1. INTRODUCTION

Heart Rate variability is physiological phenomenon of variation in the time interval between heartbeats. HRV is measured by tracing time interval between R spikes on ECG waveform in Figure1.

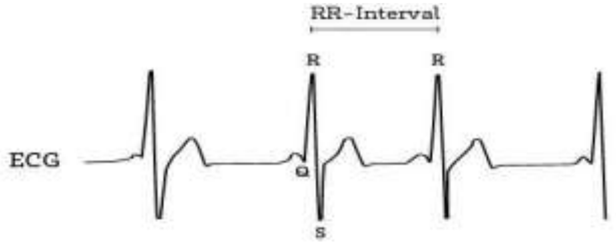


Figure1: R-R interval on ECG waveform.

Autonomic nervous system (ANS) consists of both sympathetic nervous system (SNS) and para sympathetic nervous system (PNS)[46].Where SNS increases heart rate and PNS decreases heart rate, and both of which work in correlation to maintain the body homeostasis. SNS and PNS integrate the ability of modulating heart rate and regulating QRS intervals at distinct frequencies. HRV which has been using as a diagnostic tool, for impact of Autonomic nervous system(ANS). Unlike heart rate(HR) that count number of beats per minute, HRV looks much closer in measurement of difference in time between successive heartbeats. Major fluctuations on Heart rate variability(HRV) is caused by some disorders. Various signals are used to analyse HRV i.e. ECG, PPG and BCG.

- The Electrocardiogram (ECG) reflects the various activities of the human heart and divulge hidden information in its structure. The ECG signals acquired by 12 lead ECG gives diagnostic information about the functioning of the heart. However three lead ECG is sufficient to extract HRV data to analyse the functioning of ANS[43].
- Ballistocardiography (BCG) is another non-invasive technique which produces graphical representation of vibration from pumping action of heart. BCG signals are obtained by placing sensors in chairs, bed etc.. for recording. The main drawback of this method is difficulty in detecting heartbeat[38].
- PPG is a optical technique to detect blood volume changes in peripheral circulation. It is a graphical representation of systolic and diastolic measures. Simple peak detection algorithms, are used for heart rate estimation in low amplitude photoplethysmography (PPG) signals. ECG extract, reliable HRV data within short periods of measurement. With PPG, pulse rate variation correlates with HRV for longer periods of

measurement but not for short period measurement. ECG is the reference standard signal for monitoring cardiovascular diseases. PPG sensors use ECG for heart rate(HR) comparison. Even though ECG is the accurate and reliable acquisition system, PPG is also work with the same accuracy if we use different artifacts removal algorithms[42].

In recent decades one of the major causes of death is cardiac related diseases. Heart Rate Variability analysis is emerged as effective diagnostic tool for diagnosis of early cardiac death[45]. Photoplethysmography (PPG) is a more convenient, low cost and easy, heart rate monitoring device[1]. Wearable PPG sensors support early detection of cardiovascular diseases. HRV is indirect indication, of the impact of ANS. The interest of using PPG sensor for the extraction of HRV indexes from the pulse rate variability(PRV) is rising.
(PPG signal is illustrated in figure2).

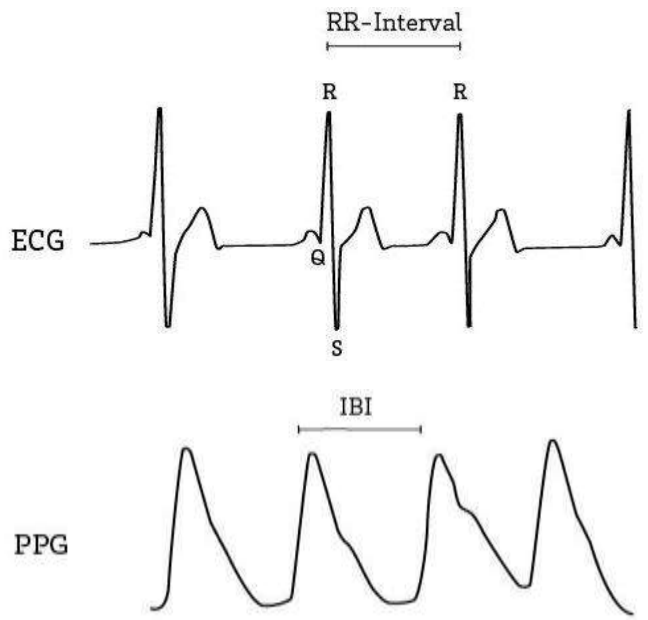


Figure 2: ECG and PPG signal

The presented paper discuss the biomedical signal (ECG, PPG and BCG) feature extraction for HRV analysis. The paper goes in detail about different acquisition module, peak detection algorithms, recent QRS detection algorithms, methods and software tools for HRV analysis.

2. PHYSIOLOGICAL RELEVANCE

Any changes in cardiac activity cause changes in HRV.

2.1 The Autonomic Nervous System(ANS)

Autonomic nervous system (ANS) consists of both sympathetic nervous system (SNS) and para sympathetic nervous system (PNS)[46]. Where SNS increases heart rate and PNS decreases heart rate, and both of which work in correlation to maintain the body homeostasis. Sympathetic activity lies in lower frequency range i.e.0.04Hz to 0.15Hz and parasympathetic activity lies in the higher frequency range of 0.15 Hz to 0.4Hz[47]. This different range of frequency allows HRV analysis to distinguish between sympathetic and parasympathetic participation events. Studies on this topic proved that when Parasympathetic activity dominates over the activity of Sympathetic, Heart Rate will decrease and HRV will increase.

2.2 HRV and blood pressure

Blood Pressure (BP) variations may cause changes or abnormalities in the cardiovascular system, especially in hypertensive than hypotensive individuals.

Lower HRV, reduced vagal tone and increase in sympathetic function were associated with hypertension patients[2][44].

2.3 HRV analysis on Smokers & Alcoholics

Studies on smokers have shown increased sympathetic activity and reduced vagal activity which can be measured by HRV analysis. Smoking impairs the cardiovascular function by its effect on ANS control [3, 4] and altered autonomic function decrements HRV.

Similar studies on alcoholics show increased HRV in both time and frequency domain independently. Acute alcohol consumption causes decrease in parasympathetic and increased in sympathetic activity[5]. A comparative study has been done on alcohol addicts and occasional alcoholics which shows alcoholic addicts have increased HRV parameters than those who are occasional alcoholics.

2.4 HRV and diabetes

Studies on diabetes patient shown that diminished cardiac peripheral nervous system (PNS) activity and severe autonomic dysfunction. Poorly controlled diabetes patients had lowered HRV and cause complications[6][7].

2.5 HRV and myocardial infarction

Acute myocardial infarction patients has dominance in sympathetic activity and reduction in parasympathetic cardiac control, which reduces thresholds of fibrillations and shows ventricular fibrillation tendency. HRV decreases in myocardial infarction patients and extra exercise does not contribute to HRV improvement after having MI[8][9]. left ventricular dysfunction causes reduced in SDRR(standard deviation between R-R interval) value and shows sympatho vagal imbalance in favour of sympathetic dominance.

2.6 HRV and gender, age

Nazy e et al[10] proved that new born girl babies have more HR variations than boys. Bonnemeir et al studied HR variation on 20 to 70 year old healthy subjects and found that HR variation is more in female than in men[11] and HRV decreases with age. Sympathetic and parasympathetic nerves maturity affects HRV .HRV increases at early stage of person life, as maturation of both these nerves increases or age of person increases HRV decreases. HRV depends both on age and sex.

2.7 HRV and Sleep

Studies on sleep shown that during non rapid eye movement (NREM) sleep parasympathetic cardiac modulation is stronger and cardiovascular system is stable[12]. In rapid eye movement (REM)sleep cardiovascular system is unstable and influenced by sympathetic activity. Sympathetic neural activity during sleep apnoea proved that sympathetic activity increases during apnoea

2.8 HRV and drugs

HRV indicate the influence of drugs on ANS. Some drugs are used to suppress the activities of both sympathetic and para sympathetic nervous system activities cause corresponding HRV response[13][14].

3. ECG ACQUISITION SYSTEM

All clinical, uses gold standard 12 lead for the ECG acquisition. Twelve lead ECG gives a more insight into the hearts in three areas (anterior=front, lateral=side, inferior=back) and it detect infarction /injury at very faster rate[15]. Nowadays most of the intensive care units use five lead, for ECG acquisition. Simple three lead and single lead ECG electrodes, determine the heart rate and cardiac rhythm at higher accuracy[16]. But accurate ST segment changes, require both frontal and precordial electrodes hence conventional 12 lead ECG machines are better in that case. Innovations in handheld devices made it possible to record electric pulses from heart in the absence of conventional ECG machines. These hand held devices are easily used at public places, houses and in offices.

4. QRS DETECTION ALGORITHMS

4.1 Pan and Tompkins(PT)

Pan and Tompkins emerged as one of the best ECG signal processing methods in 1985[17], as this method consumes very less power. This algorithm involves the pre-processing of ECG signal by band pass filter to limit the band frequency around 50HZ and signal is passed into an A/D converter at a sampling frequency of about 200HZ.(Fig.3)

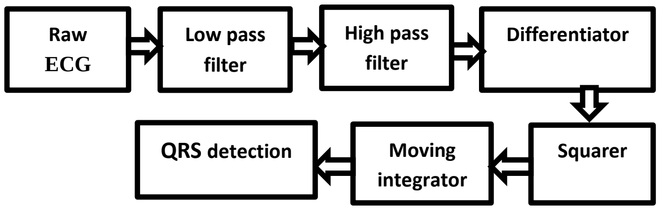


Figure 3: The block diagram represents Pan and Tompkins algorithm for QRS detection.

In this method the band pass filter is cascaded of low and high pass filters so that the low pass filter limit the operation range of an ECG signal which supresses the noise due to higher frequencies whereas the high pass filter allows only the high frequency QRS complex by reducing all types of interference and noise which impacts the quality of the signal. The filtered signal so obtained is passed through the local peak detection algorithm which detects R-peaks in the ECG signal. The algorithm adjusts by itself to the periodic changes in threshold and parameters of ECG morphology and heart rate.

The ECG signal so obtained is used as input for differentiation element which performs a five point derivative operation and if all R-peak detection is carried out properly then algorithm takes it to the next step. In case some R-peaks are missing two point derivative operation is performed and highest peak among them is considered as R-peak. The most important task is to set the correct threshold value, as problems might be faced while setting the threshold such as missing beat, undesirable interference, non-stationary variations and human source of errors.

The algorithm also uses Squaring process to detect false peaks. The QRS signals at higher frequencies are verified for their positive polarity by applying differentiator output from point to point along the signal.

$Y(n)=X^2(n)$ ....(1)

Squarer perform the operation according to the equation (1). The next step is a moving window integrator which obtains information about the area of the QRS complex. The integrator add the 32 most recent values from the squaring function by dividing sum by the 32 and average is calculated. The output is passed through peak detector and threshold setting algorithm for the identification of QRS slope. Both filtered and transformed waveforms are compared .The QRS which appear in both the processed waveforms are considered as true QRS complexes.

Hence PT algorithm involve slope, width and amplitude information for the detection of QRS complexes .wherein setting up of threshold value plays an important role which has to be done manually and may be the main source of error.

4.2 Hamilton and Tompkins

Hamilton and Tompkins modified QRS detection technique by adding some new decision rules[18]. Previously developed linear and non-linear filtering scheme were used as input to QRS detection method in pre-processing stage. The decision rule seperates true QRS complex from noisy signals and sets proper threshold value. This setting up of threshold value is important in decision rule. The algorithm involve band pass filter (combination of low pass and high pass filter) for filtering which has time averaged window for QRS complex peak detection. In Hamilton and Tompkins algorithm, in addition to peak level estimation, another decision rules are used that is search back, adaptive threshold detection and refractory blanking. Previous 8 RR intervals is stored, when QRS complex is not detected in an interval 150% of the median of RR intervals then search back method is applied. Setting proper threshold value is very much important in decision rule. Threshold coefficient of 0.182 is used for accurate results. Three estimators are used to place the adaptive threshold: the mean, median, and an iterative peak level. It also has a refractive blanking feature which maintains the period gap of 200ms between two QRS complexes. It eliminates QRS complex triggering.

4.3 Savitsky golay filters(SGF)

PT algorithm is further modified in SGF by replacing high pass filter and a differentiator SGF filter[19][20]. They reduce noise and compresses the signal by adopting least square adopting principle. The advantage of SGF is analysis of ECG in time domain and faster real time data processing.

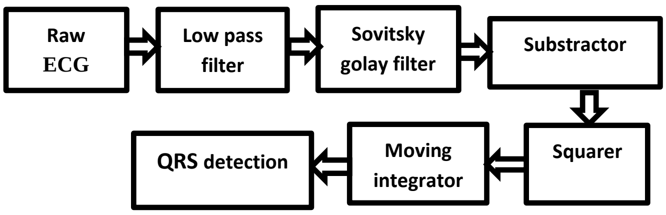


Figure 4: Block diagram represents Savitsky-Golay method for QRS detection.

$g_i = \sum_{n=-nL}^{nR} c_n f_{i+n}$ …..(1)

Basic understanding of SGFs involve average filter: where f_i - represents data values, i is the index of data points. And nL= nR, nL is the number of data points to the left of data point i and nR is the number of data points to the right. g_i - is the average of data points from *fi - nL* to *fi + nR*. Constant C_n= 1/(*nL* +*nR* +1). The aim of SGFs is to find filter coefficients C_n from equation 1. high mathematical and numerical complexity involved in finding filter coefficient and this is solved by software tools.

4.4 Phasor Transform

The QRS detection algorithm based on phasor transform [21] is recently developed method in the year 2010 and this method converts each acquired sample of the signal to complex value and store the signal information. This method has emerged as the best method in recent years because of its mathematical simplicity, low computational cost and robustness nature.Phasor transform method indicate the beginning and end boundaries of ECG signal which is useful for physicians to analyse the ECG signal.

In this phasor transform method continuous ECG samples are converted into complex numbers called as phasor.

$y[n] = R_v + j\, x[n]$….(1)

Where from equation 1: y[n] is the phasor, R_v is the real part, x[n] is the imaginary part and original ECG sample values.

Magnitude and phase are calculated by equation 2 and 3 respectively

$$M[n] = \sqrt{R_v{}^2 + x[n]^2} \text{ ….(2)}$$

$$\varphi[n] = \frac{x[n]}{R_v} \text{ ….(3)}$$

Phasor transform algorithm is emerged as more accurate and effecient methods than all other QRS detection algorithms.

5. METHODS

5.1 Time domain analysis

Variation in heart rate is evaluated by different methods, among them simplest is Time domain. In a continuous ECG recording QRS complexes are detected and beat to beat intervals (normal to normal (NN) intervals)are calculated. Simple time domain measures are mean NN interval, difference between shortest and longest NN interval etc.

Table 1: Time domain parameters

Parameter	Description
NN50	No of pairs of successive RR intervals differing by more than 50ms in continuous ECG recording.
pNN50	The proportion of NN50 count divided by total number of all RR-intervals.
MAX-MIN	Difference between shortest and longest RR-intervals
SDNN	Standard deviation of all RR-intervals
SDNN index	Mean of the standard deviations of all RR-intervals for each 5min segments in the entire ECG recordings
RMSSD	Root mean square of the differences between adjacent RR-intervals.
SDSD	Standard deviation of differences between adjacent RR-intervals
HRV index	Total number of all RR-intervals divided by amplitude of all RR-intervals

Time domain analysis distinguishes HRV indices into two types

1) Short term variability index -represent fast changes in HR
2) Long term variability index –represent slower changes (fluctuations) in HR fewer than 6min^{-1}

Both short term and long term variability indices are calculated from the RR intervals at a chosen time window. From RR intervals a number of parameters are calculated ie SDNN, RMSSD, PNN50%, SENN is the standard error, SDSD etc[22][33]. Different time domain parameter along with their description is given in table1.

Both SDNN and PNN50% implications, in patients with chronic heart failure (CHF) and acute myocardial infarction. These two time domain values used for finding out the patients risk condition.

1) High risk – PNN50 < 3%,SDNN < 50ms.
2) Moderate risk –50ms <SDNN >100ms .
3) Normal – SDNN >100ms and PNN50 > 3%. Even though Time domain measures are used for the detection of the risk condition of cardiovascular patient. Yet intensive research has to be done to set different range for the parameters.

Time domain measures are simple to calculate and based on statistical measures whereas only time domain parameters are not sufficient for HRV analysis Frequency and nonlinear methods are used along with it for better HRV analysis. If more than one analysis is used it improves the accuracy of HRV analysis.

5.2 Frequency domain analysis

Time domain parameters are easy to calculate, but it has some limitation because it relies on statistical measures and does not represent ANS activity. Frequency domain methods analyse HRV by how much a signal lies in different frequency bands(ranges). Research has identified certain frequency bands correlate with specific physiological phenomenon such as sympathetic and parasympathetic nervous system activity. Low frequency (LF)[22] and high frequency band represents sympathetic activity and parasympathetic activity of ANS respectively .

Frequency is divided into different bands depending upon their ranges, which indicate ANS activities and are discussed below.

- High frequency(HF) - 0.15HZ <HF> 0.40HZ - which indicate vagus nerve and parasympathetic activities
- Low frequency (LF) – 0.04HZ<LF>0.15HZ – which reflect sympathetic activities.
- Very low frequency(VLF) – 0.003HZ<VLF>0.04HZ – which indicate not only sympathetic but also input from thermoreceptors, chemoreceptors and others

A variety of approaches are used to extract LF, HF and LF/HF ratio and some of the methods among these are

- Fast Fourier Transform (FFT): FFT is the conventional method used by researchers for spectral analysis, because of its high accuracy in break down the complex signal into simpler components. Recent studies shows FFT technique is not suitable for processing non-linear and non-stationary signals [23][24].
- Auto regression technique: Auto regression is well suited for linear feature extraction of ECG signals. Comparative to fast fourier transform (FFT) this technique has better resolution of sharp peak and makes a smoother and elucidate curve. Even though it has significance accuracy in classification purposes, its linearity may not represent ECG non stationary nature[25].
- Wavelet transform: Different time-frequency analysis techniques are present example: short time fourier transform(STFT), hilbert huang transform(HHT), Modified wigner distribution function, bilinear time-frequency distribution and wavelet transform. In that wavelet transform has greater accuracy among other

technique and perform greatly for the analysis of nonstationary signal[26].

5.3 Nonlinear methods

Researchers use both linear time domain and frequency domain along with nonlinear techniques to interpret the HRV data. Cardiovascular system is in conjunction with the ANS activity which generate nonlinear signal and is very complex. Recent development in nonlinear techniques describe the processes generated by biological systems in very efficient way. The non linear parameters like correlation dimension (CD), largest Lyapunov exponent (LLE), SD1/SD2 of Poincare plot, Approximate Entropy(ApEn)[36],Sample Entropy(SampEn), Hurst exponent[34], fractal dimension[35], a slope of Detrended Fluctuation Analysis (DFA) [37] and recurrence plots are used for HRV analysis. nonlinear approach is not enough for HRV analysis because of length of signal recordings and numerous pattern configuration.

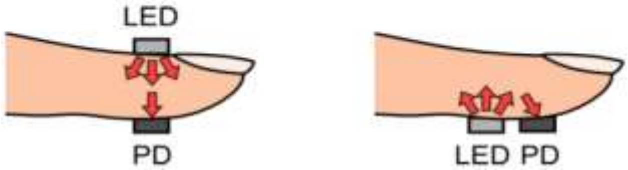
6. SOFTWARE TOOLS FOR ANALYSING HRV

1. **Kubios -** Kubios is non-commercial and freely available software for researchers and clinicians. Which performs pre- processing ,artefact correction and QRS detection.. Kubios analyse HRV in linear and nonlinear methods [27].
2. **gHRV-** gHRV is python based programming and freely available software for HRV analysis.which performs frame-based HRV analysis for an interval, a time shift and window [28] . The preprocessing stage includes outliers removal and interpolation.
3. **KARDIA -** KARDIA is matlab software for the HRV analysis. detrended fluctuation analysis (DFA) algorithm[29]is used for the detection of heart beat flustuations. KARDIA distributed free of charge, which calculate HR at any sampling rate specified by the user with different interpolation: constant, linear methods.
4. **VARVI -** VARVI is python based programming and open source software for HRV analysis.it analyse HRV in response to different visual stimuli. This type of visual stimuli based HRV analysis is used in psychiatry and other field of applications studies[30].
5. **ARTiiFACT -** It has manual and automated artifact detection and correction software available in graphical user interface. It is freely available software for research community.
6. **LabVIEW-** Laboratory Virtual Instrument Engineering Workbench(LabVIEW) provide platform for designers to build hardware and software development environment. LabVIEW is a software tool used for denoising, extracting and analyzing ECG signal[31].it has advanced signal processing and biomedical toolkit which contains several VIs, are used to extract ECG time domain, frequency domain parameters. This tool is used for HRV analysis.
7. **aHRV-** aHRV is a advanced Heart rate variability analysis software developed by Nevrokard.it import data in binary format, ASCII formats etc and export the data in .pdf, .png, .emf, .jpg formats etc[32].it includes both automated and manual data editor, and provides time domain and frequency domain analysis.

All the above mentioned softwares are used for HRV analysis and display linear and nonlinear parameters in numeric and graphical formats. Among these different freely available soft wares, Kubios of recent version 3.2 is more reliable for HRV analysis.

7. PHOTOPLETHYSMOGRAPH (PPG)

PPG is a non-invasive and cost effective optical technique for the measurement of volumetric changes in blood at peripheral circulation, in terms of the amount of infrared light received and rejected by blood.



(1) (2)

Figure 5: 1)Transmissive PPG ,2)Reflective PPG

PPG sensor consists of infrared light emitting LED and receiver photodetector or phototransistor. PPG sensors are classified into two types

1) Trans missive PPG: In this type emission module i.e. LED and photodetector are placed diametrically opposite to each other. Here the infrared LED light is passed through skin, bone and arterial blood then the infrared light is received by photodetector and is followed by filters and converters[42].
2) Reflective PPG: In this type emission module(LED) and photodetector are placed side by side or on the same side. Here the infrared LED light passes through the skin and is reflected back and received by the photodetector. This PPG sensor then followed by converters and filters for motion artifacts removal.

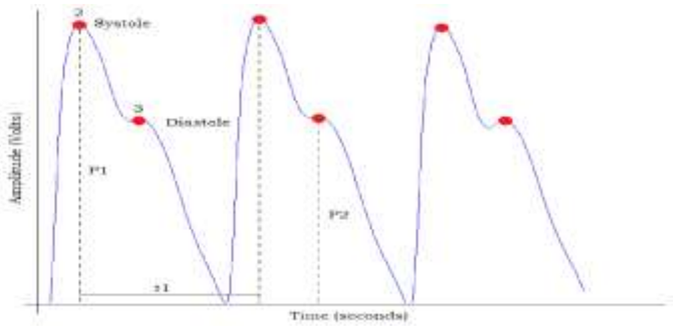


Figure 6: PPG signal analysis

Figure 6 shows the PPG graph.

- Systole: Due to the left ventricular contraction of the heart, blood flow in the signal is increased and this peak is called systolic amplitude or systolic peak.
- Diastole: The blood flows to the auricles, causing pressure to decrease in the blood vessels.It is relaxation phase[41].
- Heart rate: Time interval between beats is mentioned as t1. Heart rate is calculated by heart beat time intervals t1. $HR = \frac{60}{t1}$.......

The RR intervals obtained from ECG are used for the HRV analysis. According to the principle instead of using only ECG any of the other signal which represents accurate inter beat intervals (Heart beat) can also be used for HRV analysis. In recent years most popular technology is PPG which has similar results as ECG for HRV analysis. But in PPG instead of HRV it called as pulse rate variability (PRV). The recent research shown that, PRV obtained by PPG has a similar result as that of HRV and found the correlation of time domain and frequency domain parameters. The main drawback of using PPG in HRV analysis is its sensitivity to motion artefacts. Removing these artefacts by any new algorithm or modified algorithm is a popular research topic nowadays.

7.1 PPG signal processing and analysis

Heart rate (HR) was detected from ECG by QRS algorithms, where PPG components are extracted from low pass filtering, differentiation, zero phase filtering and threshold peak and foot detection algorithm.

Variation in pulse rate is evaluated by Linear and nonlinear methods. The methods and software tools used by ECG and PPG signal for HRV analysis are similar which are already discussed in the section 5 and 6 respectively.

8. BALLISTOCARDIOGRAPHY (BCG)

Ballistocardiography (BCG) is another non-invasive acquisition technique produces graphical representation of vibration from pumping action of the heart i.e. repetitive motions of the human body arising from the sudden ejection of blood into the vessels with each heartbeat. Ballistocardiography is a technique for producing a graphical representation of repetitive motions of the human body arising from the sudden ejection of blood into the great vessels with each heartbeat [38]. Most of the BCG measurements use different pressure sensors as a sensing device, and integrated in chairs, bed and pillows. Sensor records the body vibrations and assesses the pressure oscillations due to heart activity however it will not record movement artefacts of the patient [39]. BCG is a non-invasive method, it doesn't require any electrodes or clips to affix on the patient. Hence it helps in long term monitoring as well as stress of the patient during acquisition is minimal [40]. The main drawback being difficulty in the individual heart beat detection than in ECG due to saliency and large variability.

9. CONCLUSION

HRV is a powerful tool to assess ANS.ANS is an indirect indicator of functioning of the heart. Hence it has attracted the researches for it's easy to use. However the question lies in the authenticity of the results. The review makes an attempt to identify the bio-signals to analyse HRV being ECG, PPG and BCG. The review gives the best algorithms to analyse HRV using ECG signals. The PPG signals are as reliable as ECG in case motion artefacts are avoided[48]. BCG signal analysis has limitations as it has difficulty in individual heart beat detection and large variability.

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