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A REVIEW ON DIFFERENT METHODS TO ANALYZE HRV AND ITS CORRELEATION TO VARIOUR DISEASES AFFECTING AUTONOMIC NERVOUS SYSTEM

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ABSTRACT

The following paper reviews work on non-contact measurement of human physiological parameter, more specifically measurement of the human heart rate (HR) and consequently the heart rate variability (HRV), which is regarded to be an important indicator of autonomic nervous system activity proven to be prognostic of the likelihood of future health related events. The HRV analysis is simple and low cost method for obtaining the activities of cardiac system and in turn activities of Autonomic Nervous System (ANS). The HRV analysis is carried out mainly through linear methods and nonlinear method. The linear methods are broadly classified in to time domain method and frequency domain methods. Since, the cardiac activity is complex and a quasi-periodic nonlinear result provides more pragmatic results. The nonlinear includes measures like Detrended Fluctuation Analysis (DFA), Poincare plot and correlation analysis. There are many builtin softwares available for HRV analysis namely POLYYAN, KARDIA, RHRV, ARTiiFACT, aHRV, gHRV, HRV tool in Labview, Kubios Software etc. Among them Kubios, aHRV, gHRV are open source software, easily accessible and user friendly. The software provides the advantages of obtaining the HRV parameters with ease and reliability. In various studies HRV has been studied with conditions like myocardial infarction, blood pressure, neurological ailments, renal failure, effects of drugs, in addictions like alcohol and smoking, sleeping stages, influence of age and gender on HRV. The ability to quantify the cardiac activity in a non-contact method could prove to become an essential alternative to the conventional methods in the clinical field as well as in the more industrially oriented fields. Some of the published work so far shows that the measurement of cardiac activity in a non-contact manner is undeniably possible and in some cases also very accurate, however there are several drawbacks to the methods which need to be taken into account when performing the measurements. The following paper includes a brief description of HRV, its relation to ANS, the studies carried out for analyzing HRV in various diseased conditions. The methods used for analyzing HRV, linear and nonlinear methods, challenges and drawbacks in measuring HRV and brief description of the two usual methods, electrocardiogram (ECG) and photo plethysmography (PPG), and later on focuses on methods of non-contact measuring of HRV with webcam and smart phone cameras. Our study represents a comparative review of these methods with the conventional methods while emphasizing their advantages and disadvantages.

Keywords- *HRV(Heart Rate Variability), ANS(Autonomic Nervous System), ECG(Electrocardiogram), Webcam, Smartphone.*

I. INTRODUCTION

Measuring of human physiological parameters on a regular basis out of the hospitalisation period could become an important feature in health care, affecting healthcare policies and healthcare economics on the one hand and our daily life on the other. During the past few years a lot has been learned about diseases at a genomic level, creating possibilities of an early detection of illness symptoms and improving the treatment process itself. Amongst other findings, numerous studies have shown a significant relationship between the autonomic nervous system (ANS) and cardiovascular mortality .More precisely, perturbations of the ANS and its imbalance were discovered to indicate impending cardiac diseases, which may lead to a sudden cardiac death, one of the leading causes of cardiovascular mortality [1].

The ANS function is necessary for the maintenance of homeostasis. It operates independently of voluntary control through the sympathetic and the parasympathetic nervous systems which often function in an antagonistic manner. The autonomic processes are involved in the control of many bodily functions, such as thermoregulation, blood pressure, regional blood flow, etc. The status of the ANS can therefore be assessed by observing several

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physiological parameters which can be obtained and processed with different measuring and analytical methods [2]. One of the markers for ANS assessment that has caught the attention of the profession is called the heart rate variability (HRV). Next to the clinical settings (e.g. diabetic neuropathy, myocardial infarction, sudden cardiac death, etc.) this parameter is also used in several other fields, such as sports science and ergonomics [3, 4].
Heart rate and heart rate variability HR is defined as the rate of occurrence of cardiac beats in a specific period of time, usually expressed in beats per minute. Although the occurrence of cardiac beats could be triggered by the electrical pulses generated within the sinoatrial (SA) node, the actual frequency of heart's electrical and contractile activity is in the most part modulated by the ANS. This neural regulation causes variability in the HR in the active as well as the resting state. The variability should be high in the normal physiological state of an individual and should only erode with age or progression of the disease [1, 5].

1.1 Heart Rate and Neural Control

The periodic and spontaneous depolarization of sinoatrial node determines the heart rate. Though, to initiate heart beat there is no need for neural innervations but depolarization of sinoatrial node depends on sympathetic and parasympathetic autonomic nervous system(ANS), reflexes, intrinsic cardiac neurons and on respiration modulation. The electrical activity of the heart and cardiac contractility are influenced by neural systems. The neural system regulates the inotropism(contractility), cardiac chronotropism(Heart Rate) and dromotropism(conduction) as required to the needs of the body.

1.2 Sympathetic Nervous System

The origins of sympathetic nerve fibers are from preganglionic neurons of spinal cord intermediolateral column through (T1-L2) lumbar regions. Most sympathetic nerve fibers synapse with efferent neurons of postganglionic region after passing through white rami. The sympathetic neurons innervate viscera and the blood vessels through the post ganglionic neurons.

1.3 Parasympathetic Nervous System

The origin of parasympathetic nerve fibers are from the preganglionic neurons situated in sacral area(S2-S4) and brainstem. Parasympathetic nerves passes through the head to abdomen with in cranial nerves. The cranial nerve gives the innervations of parasympathetic to lungs, heart and some regions of abdomen. About 80 percent of axons of this nerve are afferent, remaining axons are efferent. The classical studies believed that parasympathetic innervations have little to no effect on ventricular myocardium, but the studies showed well established effect of parasympathetic innervations on ventricular myocardium. It is parasympathetic nerves inhibits the free moving neurotransmitter released from the sympathetic nerves. This indirect effect of parasympathetic on ventricular myocardium influences the cardiac functions [5-7]. The acetylcholine is released with the simulation of vagal system, resulting in atrial contractility, myocardial conduction, decrease Heart Rate (HR) and ventricular contractility [5-7].

II. MEASURES

In addition to the basic measures of the HR, such as beats per minute (BPM), variations in the HR can be evaluated by numerous methods and measures derived. These measures of HRV can be divided into two classes: the time-domain and frequency-domain measures of HRV.

2.1. Time Domains

Time-domain measures can be derived from direct measurements of the normal-to-normal intervals (NN in tervals) or instantaneous HR, or from the differences between NN intervals. Within the included studies, reported time-domain measures include the mean NN interval
in milliseconds (ms) (12), the mean standard deviation (SD) of all NN intervals (SDRR or SDNN in ms, (8, 11, 12, 14, 15), the square root of the mean of the sum of the squares of differences between adjacent NN intervals (RMSSD in ms, (8, 11, 12), the mean of the SDNN of all NN intervals (SDNN index or SDNNi in ms (12)), or the number of pairs of adjacent NN intervals differing by more than 50 ms divided by the total number of all NN intervals (pNN50 in %, (8), or SNN-50 (12)). Besides these frequently used, authors reported the corrected SDRR (corSDRR, SDRR corrected for HR as described in (14), and SD of differences between successive R-R intervals (SDDRR [14]), the SD of the average of valid N-N intervals (SDANN, (12)), or the inter-quartile range of the R-R intervals (16).

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2.2. Frequency Domains

Parametric and nonparametric methods to analysis the power spectral density (PSD) of HRV, allow the calculation of different spectral components of short and long term recordings of HRV. From short-term recordings, three different main spectral components are distinguished: very low frequency (VLF ≤ 0.04 Hz), low frequency (LF, usually 0.04-0.15 Hz), and high frequency (HF, usually 0.15-0.4 Hz) components. Furthermore, an ultralow frequency component (ULF) can be derived from the spectral analysis in long-term recordings (e.g. 24 hours). Depending on the length of the recording different frequency-domain measures with different frequency bands are reported within the included studies including the power in HF (8, 10-12, 14, 17, 18); the power in LF (10-12, 14, 15, 17, 18); the power in ULF (12), or total power (11, 12, 14, 17, 18). Besides these, several studies include a mid-frequency-band (MF [15, 17, 18]) or a very-low-frequency band (VLF) besides the ULF (12). Traditionally, the ratio between LF and HF (LF/HF ratio) serves as another measure of HRV and was used frequently by the included studies (10, 14, 15). Generally spectrum are obtained using FFT(Fast Fourier Transforms), Fast Fourier Transform. The FFT is a faster version of the Discrete Fourier Transform (DFT). The FFT utilizes some clever algorithms to do the same thing as the DTF, but in much less time. The DFT is extremely important in the area of frequency (spectrum) analysis because it takes a discrete signal in the time domain and transforms that signal into its discrete frequency domain representation. Without a discrete-time to discrete-frequency transform it is difficult to compute the Fourier transform with a microprocessor or DSP based system. DFT is defined as

x(n)=X() 1

where, X()= 2

Furthermore, several studies report other ratios, such as the LF+MF/HF [15, 18] the LF/total or HF/total (14). Besides these frequently used, one study reports the mean heart rate (HRm) and variance (HRv), and QT interval mean (QTm) and variance (QTv), and a normalized QT variability index (QTVI), as described elsewhere (9). Furthermore, a single study reports the geometric triangular index (HRVi), which is the total number of all N-N intervals divided by

the height of the histogram of all N-N intervals measured on a discrete scale with bins of 7.8125 ms, and with no adjustment for recording length (13).

2.3 Nonlinear Methods

Because of the nonlinear heart dynamics, conventional time and frequency domain parameters of HRV may not always represent the nonstationary characteristics of ECG. Nonlinear methods such as the Poincare plot, detrended fluctuation analysis (DFA), tone/entropy analysis and HR complexity analysis are newly developed tools used for identifying nonlinear patterns within ECG data [13-18].

2.3.1 Poincare Plot

The Poincare plot is a scatter plot of *RR*n vs. *RR*n+1 where *RR*n is the time between two successive R peaks and *RR*n+1 is the time between the next two successive R peaks. When the plot is adjusted by the ellipse-fitting technique, the analysis provides three indices: the standard deviation of instantaneous beat-to-beat interval variability (SD1), the continuous long-term R/R interval variability (SD2), and the SD1/SD2 ratio (SD12)15. On the Poincaré plot, SD1 it is the width and SD2 the length of the ellipse. In addition to this conventional plot (RR_{n+1} vs. RR_n), we also used the generalized Poincaré plot with different intervals, including the m-lagged Poincaré plot (the plot of RR_{n+m} versus RR_n). The values of SD1 and SD2 were calculated for lag = m from the relations SD1 = (Φ(m) − Φ(0))1/2 and SD2 = (Φ(m) + Φ(0))1/2, where the autocovariance function Φ(m) is given by

Φ(m) = E[(RRn − RR) (RRn+m − RR)]

and RR is the mean RRn14. For the purpose of our study, we set m at [1, 5, and 9]. We then extended our analysis to reveal the association between these standard deviation (SD) values and m by using the Padé approximation[19]. We assumed a simple form of the Padé approximation for SD values as the ratio of polynomial in M of degree one.

2.3.2 Detrended Fluctuation Analysis

Another analytic method to assess long-term correlation in the R–R-time sequence is based on DFA 20. The measure of correlation was given by a scaling exponent (α) of the fluctuation function F(τ) ≈ τα. The fluctuation function F(τ) was computed as follows. For a given time sequence R(ti), ti = iδt, where δt is the characteristic time interval for the sequence and i = 1, N is an integrated time series, r(ti) was defined as r(ti) = Σij [R(tj) – <R>], i = 1,N, where <R> is the mean of R(ti). The integrated series was divided into segments of equal duration, τ = n δt and a linear function used to fit the data within each segment. The fluctuation function F(τ) was calculated as the root

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mean square fluctuation relative to the linear trend and alpha was obtained by fitting the data to a power law function. It has been observed that an acceptable estimate of the scaling exponent alpha (from DFA) can be obtained from analysis of data sets with 256 samples or longer (equivalent to approximately 3.5 min of RR data at a heart rate of 70 beats/min). The analysis of RR data from an ECG recording period of 10 min was therefore expected to provide an adequate measure of the scaling exponent 21. However, the alpha value obtained from this calculation may be under the mixed influence of both short-term scaling, reflecting parasympathetic control, and long-term scaling, reflecting sympathetic control, and thus may fail to fully distinguish parasympathetic and sympathetic influences. A separate analysis of both short- and long-term scaling is supposed to nullify the mutual effect and reveal the exact scaling variation 22. Thus, we analyzed separate alpha values, short-term αs and long-term αl. For αs, data from 25 beats were included, whereas for αl, data from 30 to N/4 beats were included.

2.3.3 Correlation between successive differences in RRn interval

The coherence of the RRn interval can be accessed from the map of interval variation: where <RRn> is the mean interval. This plot is expected to show the correlation between the variability of three consecutive R–R intervals.

$rr_{n+1}=$ vs $rr_n=$

Autocorrelation of fluctuation of RRn

We explored the autocorrelation of the deviation of RRn from the mean <RRn>. The autocorrelation function C(m) of a particular subject was calculated from

C(m)=

where the deviation is ΔRRn = RRn – (RRn) and N is the total number of RRn intervals.

3.1. Conventional methods for cardiac activity measurement

In order to detect HRV changes over longer periods of time, a large volume of data needs to be collected and analyzed. Suitable data for further analysis is normally obtained with a Holter monitoring out-patients, which is a portable device for continuous monitor-ing of various electrical activity of the cardiovascular system for at least 24 h. More traditionally, the data is collected with one of the two conventional methods in clinical use, the ECG or the PPG. The ECG on the one hand is considered to be one of the oldest diagnostic tools still used in medicine today with first recordings dating back as early as 1903. It is a clinical tool used in the field of cardiac abnormalities evaluation and is characterized by its high accuracy and easy interpretation. Despite the difficulties, the ECG is considered to be an optimal way of measuring the inter-beat intervals (IBI), which are intervals between two adjacent heart beats. The method uses conductive Ag/AgCl electrodes attached to the patient's body in a predefined and standardised fashion in order to detect and record the difference in the electric potential between different electrodes generated by the electric activity of the cardiacmuscular fibres over a period of time. In the past the recording waspresented in a graphical way on a standardised paper. Nowadays the data is stored in a digital form and can be displayed on a dig-ital screen or transferred to another digitalised device for further analysis [18,19].

3.2. Experimental non-contact methods for cardiac activity measurement

The demand for ubiquitous measuring of human physiological parameters is ever increasing not only in the medical field (e.g.monitoring of hospitalized patients, home health care, rehabilitation, nursing of elderly [23,24]) but also in several commercially oriented fields, such as automotive industry (vital sign monitoring of the driver [25,26]), psychology (measure of stress response[23,27–31]), sports (optimisation of training [23,32]) and even in the field of man–machine relation (emotional communication[33]). In order to be able to conduct measurements in such diverse fields, the existing contact methods for obtaining parameter values with the known limitations would seem inadequate in some cases.

A non-contact method (Fig. 1) would present a more appropriate solution for such instances where the goal is to acquire only the IBI and not the exact details concerning cardiac electrical conduction that ECG offers. In the past years several innovative non-contact methods for measuring cardiovascular parameters, particularly the HR and HRV, have in fact been studied world-wide.

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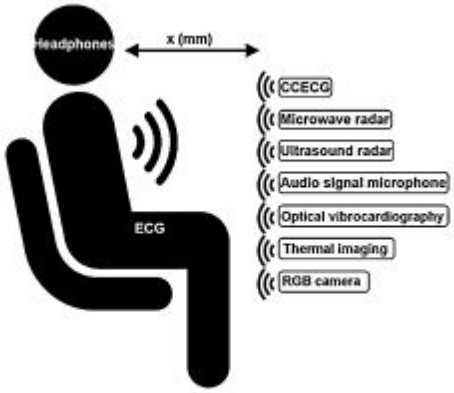

Fig. 1. A representation of the proposed non-contact methods for HRV measurements found in the literature. There is an explicit air gap between the measuring sensor and the human body. The size of the air gap varies for different non-contact methods.

III. Methodology of IBI measurement with different methods

Due to the nature of the functioning of the cardiovascular sys-tem on the one hand and the specific characteristics of the human body on the other hand, the IBI can be assessed directly or indirectly through specific physiological parameters with several different methods. Within this chapter, a brief overview of the known possibilities is given, substantiated by examples found in the publishedliterature.

4.1 HR from speech

Speaking is the most basic form of communication between people. Next to the basic expression and linguistic information, the voice output also includes hidden organic and biological information [32]. In fact, the human heart rates are dynamically related to the variations of vocal cord parameters via the larynx, which is in directly connected to the human circulatory system [32]. Due to this fact, it should be possible to detect human heart activities by extracting appropriate frequency characteristics from the changes in human speech [32].

Table 1. The list of novel non-contact measuring methods for HR (and consequently HRV) measurement.

Measuring method	Experimental method	Sensors used
Electrocardiogram	Contact,	Conductive electrode
Photoplethysmography	Contact,	Phototransistor
Headphones	Contact,	Coil within the head-phone
Capacitively	noncontact	Capacitively coupled electrodes
Microwave	noncontact	Microwave sensor
Ultrasound	noncontact	Ultrasound sensor
Optical	noncontact	Laser
Thermal	noncontact	Thermal imaging camera
RGB	noncontact	Digital camera
HR from Speech	noncontact	Standard microphone

4.2 Thermal imaging

All surfaces with temperatures over 0 K emit electromagnetic radiation. The amount of emitted energy at a particular wavelength depends on object's or subject's temperature and emissivity. The human skin is considered to be an excellent emitter/absorber of thermal energy with an emissivity value between 0.95 and 0.98[34]. At a regular human skin temperature of about 300 K, the emit-ted radiation is in the far infrared (IR) part of the spectrum, which is not visible to the naked human eye. Thermal imaging is an example of infrared imaging science. It is a passive (does not emit energy), non-contact method for measuring the emitted radiation in the IR range of the electromagnetic spectrum and produces an image of that radiation in the form of a thermograph.

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4.3. RGB imaging

The cardio-vascular pulse wave travelling through the body periodically causes the vessel walls to stretch. The volumetric changes that are a result of fluctuations in the amount of blood or contained air within the human body can be measured by means of a PPG. These fluctuations modulate the absorbance of light passing through a given tissue volume, which is detected by the mentioned measuring method. PPG is performed with a dedicated light source and considers the ambient light as the source of noise. Recent studies have shown that some cardiovascular signals (e.g. HR, IBI) can be acquired remotely from a distance of several metres by processing a video file of a human face obtained with standard cameras with ambient light as the illumination source. Furthermore, the studies show that the method can be extended for simultaneous HR measurements of multiple persons [39,40].

The RGB sensor of the used camera is able to pick up a mixture of the reflected plethysmographic signal with fluctuations in the amount of reflected ambient light. This phenomenon is again caused by volumetric changes in the facial blood vessels during the cardiac cycle and thus indicates the timing of cardiovascular events [39,40].The novel approach is based on automatic face tracking and localisation of measurement ROI on the one hand and recovery of underlying source signal of interest on the other. In this case, the signal in question is the cardiovascular pulse wave that spreads throughout the body. Its recovery is achieved with Blind Source Separation (BSS) by Independent Component Analysis (ICA).The idea for distant measurement of PPG parameters was presented in several papers [41–43]. However, the efforts lacked rigorous physiological and mathematical models for computation. Furthermore, motion artifact presented noise within the same frequency band as the signal of interest, thus rendering linear filtering ineffective.

4.4. Capacitively coupled ECG

The activities of human organs, such as the heart, brain, mus-cle, etc. result in bioelectric signals. Bioelectric signals accompany all biochemical processes and are defined as electric potentials between points in living cells and can be measured with several techniques, including the ECG. Compared to other signals, the amplitude and the bandwidth range of heart signal (0.1–0.5 mV; 0.5–100 Hz) is amongst the largest and as such appropriate to mea-sure in a non-contact manner [40]. In order to detect such relatively small signals, a sensor with high sensitivity and low susceptibility to ambient interferences needs to be applied.

IV. CONCLUSIONS

HRV analysis is a significant tool for assessing the functions of Autonomic Nervous System(ANS). The cardiac and ANS activities significantly changes in diseased conditions. These changes can be easily assessed using HRV analysis. HRV analysis gives the linear and nonlinear parameters of the HRV. Linear parameters are broadly divided in to time-domain and frequency domain parameters. Nonlinear parameters includes correlation coefficient, detrended fluctuation analysis and poinecare plot. These are various softwares available for extracting HRV parameters like KARDIA, RHRV,aHRV,gHRV, kubios software etc, making HRV analysis to be simpler. This work reviews HRV analysis in different diseased conditions, like myocardial infarction, blood pressure, neurological ailments, renal failure, effects of drugs, in addictions like alcohol and smoking, sleeping stages, influence of age and gender on HR. The vital physiological signals required to obtain HRV are ECG and PPG. Both of these are contact methods and the challenges of obtaining these signals are discussed. The noncontact methods of measuring cardiac activity have wide applications in both clinical and commercial applications. The home-health care is emphasizing on measuring the physiological signals at home itself. Hence there is a growing interest in the field of easy and noncontact measuring of cardiac activities. Because of the potential benefits in various fields, many works is going on worldwide, in search for new sensors, novel methods of analysis and improving the already existed ones. Noncontact methods of HRV analysis using webcam and smartphones are discussed and their advantages and disadvantages are quantified. In further, the HRV analysis using noncontact methods can be used to obtain HRV in different diseased conditions and to statistically quantify. Also, the ROI taken for measuring HRV is generally the face region. ROI can be changed to the other parts where more pulsatile changes can be derived.

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