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A Survey on the Scope of Cardiac Arrhythmia Classification using BCG

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***Abstract*—Heart disease is one of the main factors causing death in the developed countries. If long term monitoring of heart is possible, we can control the death due to heart diseases to an extent. Ballistocardiography (BCG), a non-invasive method can be used for long term monitoring of the heart. This review paper provides an overview of various methods that has been used for BCG acquisition and cardiac arrhythmia classification using BCG. The main aim of this paper is to find a suitable method for the processing and classification of BCG signals so that the result is more suitable for the detection of cardiac arrhythmia.**

***Index Terms*—Ballistocardiogram, cardiac arrhythmia, artificial neural networks.**

I. INTRODUCTION

Heart disease is one of the main factors causing death in the developed countries. A lot of electronic and computer technology have been developed to help cardiac performance monitoring and heart disease diagnosis. Among these methods, Ballistocardiography(BCG), a non-invasive method, has an interesting feature that no electrodes are needed to be attached to the body during the measurement. Ballistocardiography(BCG) represents the mechanical activity of the heart. It attracted a lot of interest among the cardiologists initially but interest in this method faded later because (i) the BCG devices were complicated mechanical devices and (ii) the signal analysis methods of BCG did not develop as well as those of the electrocardiography (ECG)[1]. New sensor materials, such as the EMFi sensor (electromechanical film sensor) and accelerometer are used to acquire BCG signals[2]. The developments of signal analysis and processing methods like wavelet analysis enable much more efficient analysis of these signals[3]. A large number of Bio-signal classification methods have been developed including principle component analysis, Fourier analysis, linear filtering autoregressive modeling, neural networks, and support vector machines [1].

Cardiac arrhythmia or irregular heartbeat is any of a group of conditions in which the activity of the heart is irregular or is faster or slower than normal. The heartbeat may be too fast

(over 100 beats per minute) or too slow (less than 60 beats per minute), and may be regular or irregular. A heart beat that is too fast is called tachycardia and a heart beat that is too slow is called bradycardia. Although many arrhythmias are not life-threatening, some can cause cardiac arrest. Arrhythmias can occur in the upper chambers of the heart (atria), or in the lower chambers of the heart, (ventricles).Some common arrhythmias are premature atrial contractions, atrial flutter, atrial fibrillation, atrial tachycardia, premature ventricular contractions, ventricular fibrillation and ventricular tachycardia.It would be helpful for both doctors and patients, if the heart condition could be monitored regularly at the home before making the decision whether or not it is necessary to visit the hospital. These lead to the requirement of portable systems with reduction in size, weight and power consumption for the heart monitoring and diagnosis at home. BCG can be used for such long term monitoring at home, by classifying the signals using different methods including neural networks and wavelets.

II. BACKGROUND

A. BALLISTOCARDIOGRAM

Ballistocardiogram(BCG) is the representation of the mechanical activity of the heart. It represents repetitive motions of the human body due to the sudden ejection of blood into the blood vessels from the heart, which is caused by the mechanical movement of the heart, with frequency 1-20 Hz and can be recorded by non-invasive methods. The Ballistocardiograph consist of eight fiducial points (G, H, I, J, K, L, M and N) as shown in fig.1

The H wave associated with contraction of the heart is an upward deflection which is relatively small. During heart disease, it may become large in amplitude, equal or exceeding the height of the J wave. The I wave is associated with ventricular ejection. The peak of the J wave occurs between 0.22 and 0.26 second after the onset of the QRS complex of the electrocardiogram. In abnormal situations the I and J waves are decreased in amplitude, the I wave may not be evident, the J wave becomes thick and notched and its peak is delayed to 0.28 second or even longer after the onset of the QRS. The K wave represents aortic deceleration. The K wave is increased in amplitude and attains an earlier trough with increased peripheral resistance and arterial inelasticity as in hypertension, and arteriosclerosis of the aorta with aging and subsequent diastolic waves in the ballistocardiogram represent forces in the aorta[4]. A method was presented to detect arrhythmic episodes[14] by analyzing an interbeat interval series derived from a BCG signal obtained using a bed sensor. The entire system (bed sensor and analysis procedures) can constitute an innovative tool for home monitoring of patients and subjects at risk of developing cardiac pathologies. In fact, the bed sensor is completely not invasive and not obstrusive and allows home recordings without interfering with the subject's daily life. Further, the automatic analysis procedure allows the identification of critical events and can produce alarms only in case of need. Algorithm[14] was applied on a single subject but it will be necessary to test it on a higher number of subjects in order to obtain more reliable results.

A framework [15] for feature extraction technique based on dual tree complex wavelet transform (DTCWT). The feature set comprises of complex wavelet coefficients extracted from the 4th and 5th scale of DTCWT decomposition and four other features (AC power, kurtosis, skewness and timing information). This feature set is classified using feed forward neural network. Five types of ECG beats (Normal, Paced, Right Bundle Branch Block, Left Bundle Branch Block and Premature Ventricular Contraction) are classified from the MIT BIH arrhythmia database. Four features extracted from QRS complex of each cardiac cycle concatenated with the features extracted from the 4th and 5th decomposition levels of DTCWT, is used as total feature set.The performance of the method is compared with DWT based statistical features.This methodology can be used in telemedicine applications, arrhythmia monitoring systems, cardiac pacemakers, remote patient monitoring systems.

B. CARDIAC ARRHYTHMIA

Cardiac arrhythmias are disturbances in the normal sinus rhythm of the heart, which means irregularity or abnormally fast rates (tachycardias) or abnormally slow rates (bradycardias). Atrial premature beats are produced by abnormalities of atrial electrical activity that discharge the atria earlier than normal function of the sinus node. Ventricular premature beats occur during myocardial infarction and more frequently in those who have sustained greater amounts of myocardial damage. Atrial flutter is a relatively uncommon tachyarrhythmia that develops in adults with various types of heart disease or severe pulmonary disease, after cardiac surgery. Atrial tachycardia is another relatively uncommon tachyarrhythmia produced by automatic foci in the atria. The tachyarrhythmias that originate in the ventricles, monomorphic and polymorphic ventricular tachycardia and ventricular fibrillation, threaten the lives of adults more often

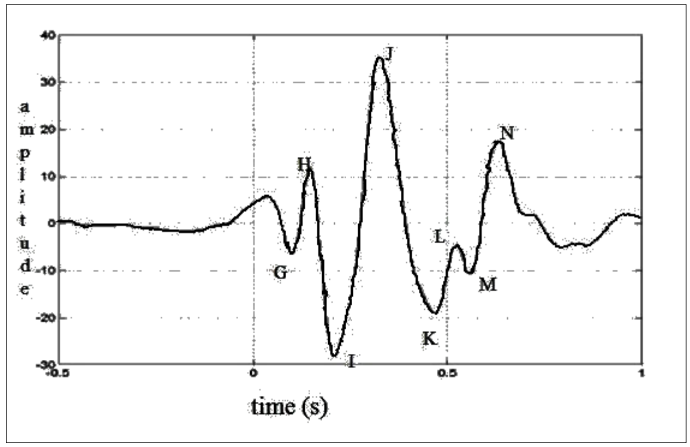

Fig. 1. Example of BCG signal including spikes and wave complexes called G,H,I,J,K,L,M and N components [1]

than do any other tachyarrhythmias. Ventricular fibrillation is an immediately life threatening ar-rhythmia in which the heart's electrical activity and associated contraction become disordered and ineffective. Ventricular tachycardia is a rhythm characterized by wide wave and premature contractions in a row.

III. SIGNAL ANALYSIS

A. DATA ACQUISITION

New sensor materials, such as the EMFi sensor (electromechanical film sensor) and accelerometer can be used to acquire the BCG signal[2].

1) EMFi sensor : The electromechanical film sensors are mainly used for acquiring BCG raw signal. Here a hospital bed was designed to allow the sensing of forces acting perpendicular to the surface of the bed. This was achieved by attaching four strain gauges to one slat of the beds slatted frame. Located at the center of the slat, these strain gauges form a full Wheatstone bridge that measures the deformation of the slat. The instrumented slat was installed under the subjects thorax in order to optimally record cardiopulmonary activity. An ordinary mattress was placed on top of the slats. Data were acquired by means of a 12-bit analog-to-digital converter using a sampling rate of 128 Hz[4].

2) Accelerometer : One method to noninvasively measure the forces generated by the heart is to measure the tiny displacements of the skin by attaching an acceleration sensor, called accelerometer, directly onto the skin of the person[5]. The method for coupling the sensor to the skin, the sen-sor properties like sensitivity, dimensionality, noise rejection, weight and supporting structures and wiring solutions has their own effect on the measured signals. The ADXL202 and

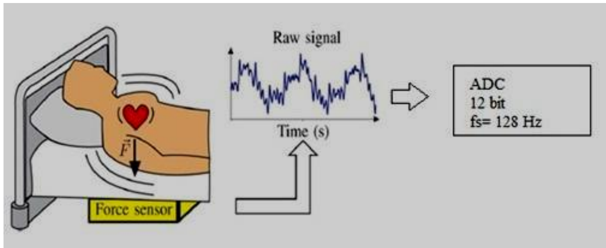

Fig. 2. Overview of the operating principle of a general bed mounted BCG system [4].

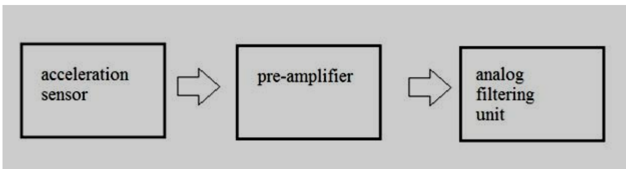

Fig. 3. Internal structure of accelerometer[2].

MXA2500U accelerometers are commonly used. As a whole, the sensor consists of the acceleration sensor, the preamplifier, and an analog filtering unit [2].

B. BCG SIGNAL EXTRACTION

Different algorithms are used for the extraction of BCG signal [6][4].

[1] Blind BCG segmentation : Alireza Akhbardeh et.al. mentioned about this algorithm in their new algorithm[6]. It helps in automatic detection of BCG signal.The standard blind segmentation method performs BCG segmentation using BCG itself, without using any other synchronization signal such as ECG, in the following steps: 1) Normalization: normalize the BCG signal to the range [-5, 5] Volt; 2) Filtering: use a band pass filter with 2 and 20 Hz cutting frequencies to find a clean, normalized BCG signal; 3) Extract a coarse BCG signal using a narrow band pass filter with 1 and 2 Hz cutting frequencies. Synchronization points: detect local maxima and peaks of absolute BCG coarse signal which are between a lower volt and upper amplitude threshold as synchronization points. Synthesize BCG cycles: To have uniform BCG cycles with length of 2500 samples (1.2 seconds), set the computed synchronization points as central points of synthesized BCG cycles and then peak 1250 BCG samples before and 1240 BCG samples after those central points.

2)Bseg++, modified blind BCG segmentation : Alireza Akhbardeh et.al. introduced this algorithm in [6]. In this algorithm the following modifications are done, Changed the

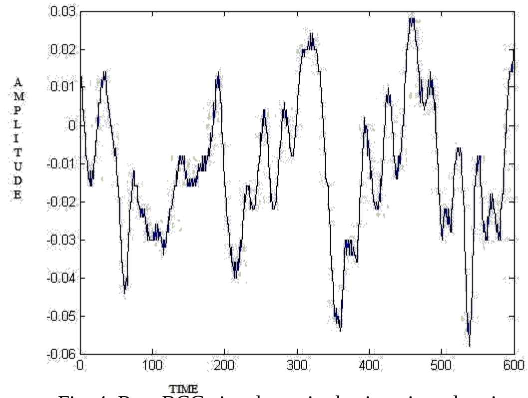

Fig. 4. Raw BCG signal acquired using piezoelectric sensor from Govt. Engg. College Wayanad database.

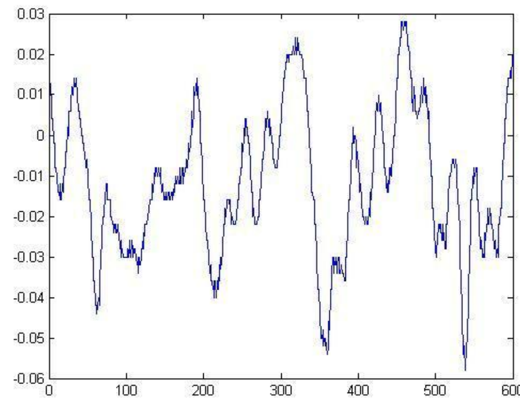

Fig. 5. Raw BCG signal acquired using piezoelectric sensor from Govt. Engg. College Wayanad database. details of object : age = 24 years, gender = male , healthy

step 4 to: a) Use synchronization points (cntr) extracted using BCG coarse signal to search local minima of BCG signal in the range of [cntr-R, cntr+R] and set their indexes as final synchronization points, where R is search range. We can set empirically 0 .1 d R d 0 .5 second; b) Ignore final synchronization point p(i) if p(i)¡ p(i-1)+ k1*Fs, where K1 and Fs are a user- defined time range and Fs is sampling rate (2000 samples/second). To detect H-I-J components of the BCG signal the following steps are added to the algorithm: 6) Set final synchronization points as I waves of extracted BCG cycles. 7) Use indexes of I waves (Iindx) to search local maxima of BCG signal in the range of [Iindx-M, Iindx] and set their indexes as H waves of extracted BCG cycles, where M is a search range. We set empirically 0 .1 M 0 .5 seconds.

8) Use indexes of I waves (Iindx) to search local maxima of BCG signal in the range of [Iindx, Iindx+N] and set their indexes as J waves of the extracted BCG cycles, where N is a search range. We set empirically 0 .1 N 0 .5seconds.

3) Okada Algorithm : In order to extract good BCG signal, multiple filters are used. It cosists of FIR filters, Gaussian

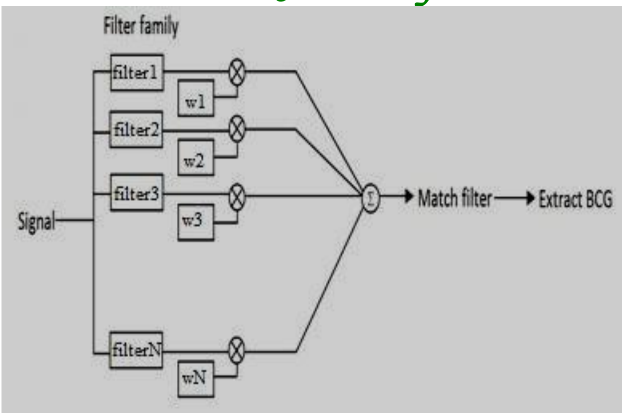

Fig. 6. Okada Algorithm [4].

wavelets, Daubechies wavelets. Each filter received its weight according to the comparison criterion of the OKADA algorithm. The BCG signal is then filtered with Moving average filter and Low pass filter. The square difference of the filter signal is calculated then based on the comparison criterion the beat to beat interval of the BCG signal is detected[4].

4)Continuous Local Interval Estimation (CLIE) Algorithm BCG signals are recorded using an EMFi foil sensor on top of the regular mattress. The beat-to-beat interval estimation is performed completely unsupervised. It is estimated by using a short adaptive analysis window and three different methods are combined to estimate the main periodic component for each window. The analysis window is shifted across the signal using increments that are short with respect to typical interval lengths, so that each interval appears in the multiple consecutive analysis windows. The power spectral densities can be estimated. BCG-derived beat-to-beat intervals can regularly contain missing or unreliable segments due to motion artifacts. These segments can easily be omitted when estimating the PSD[4]

5) BEAT Algorithm : The raw BCG signal is first preprocessed by applying a second order Butterworth high-pass filter. This filter has a 3-dB cut off frequency of 1 Hz so that the low-frequency respiratory components can be removed. This frequency provides a good trade off between the pulse shape retaining and suppression of undesired artifacts due to respiration. A short segment of the filtered signal is then analyzed to determine the features of the heart beat in the training phase. The remaining signal is scanned for heart beats using the features that were extracted during the training procedure. This is done in the beat detection phase. This results in a list of estimated heart beat locations. Finally the estimated heart beat locations are used to produce a refined list[4]

C. BCG ANALYSIS

1) FOURIER TRANSFORM : The Fourier transform is a mathematical transformation employed to transform signals between time (or spatial) domain and frequency domain, which has many applications in physics and engineering. The short-time Fourier transform (STFT) is a Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. The STFT method can analyze a non-stationary signal in the time domain through a segmented algorithm. Through a moving window process, the original signal is broken up into a set of segments, and each segment is processed by the conventional Fast Fourier transform (FFT) algorithm. The drawback is that once you choose a particular size for the time window, that window is the same for all frequencies. Many signals require a more flexible approach where we can vary the window size to determine more accurately either time or frequency. It can be used to obtain time varying spectral representation of a signal [7].

2) PRINCIPAL COMPONENT ANALYSIS : Principal com-ponent analysis (PCA) is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly un-correlated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the high-est variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding component. It can be used for feature extraction and to reduce the number of elements in the output. It requires prior knowledge about the statistical distribution of data samples [8][9][10][11].

3) WAVELET ANALYSIS: It is a windowing technique with

variable - sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. One major advantage offered by wavelets is the ability to perform local analysis to analyze a localized area of a larger signal. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Furthermore, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or de-noise a signal without appreciable degradation. A wavelet is a waveform of effectively limited duration that has an average value of zero. Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. It can be used to extract the features [9][1][8][3][12][13][11]. Different wavelets like Symmlet wavelet[13], Spline wavelet , Haar wavelet, and Daubechies wavelet[1] can be used for wavelet analysis. This analysis requires no prior knowledge of the statistical distribution of data samples and the computation complexity and training time are reduced[8].

D. CLASSIFICATION METHODS

There are different methods to classify the BCG signals[16][7][8]

1) Naive Bayes (NB) : An NB classifier models the process producing the data as a random Gaussian process. Unknown probabilities are estimated under the assumption of stochastically independent features. Evaluation is then conducted via the Bayes theorem. It trains and classifies very quickly [7].

2) Linear Discriminant Analysis (LDA) : LDA tries to find a linear hyperplane separating the class instances. It is based on the assumption that instances from each class are normally distributed with equal covariances for each class[7].

3) Quadratic Discriminant Analysis (QDA) : Closely related to LDA, QDA separates classes using quadratic surfaces instead of a linear one. Like LDA, it is also based on the assumption of normally distributed class instances but drops the assumption of equal covariance matrices[7].

4) Support Vector Machine (SVM) : An SVM constructs a maximum-margin hyperplane separating the class instances. To achieve this, the data might have to be projected to a very high dimensional space which is computationally expensive. Using a kernel function, the computational burden can be reduced since an explicit computation of the projection is not required[7][11].

5) Bagged Trees (BaT) : The BaT algorithm combines a large number of decision trees and assigns class labels to unknown instances. Since the decision trees have been trained on different bootstraps of the training data, their classification results differ and ideally augment each other[7] .

6) Random Forests (RFs) : RFs are very similar to BaT but introduce a new parameter m, which decides how many randomly chosen features are considered when constructing each split of a decision tree[7].

7) Boosted Trees (BoT) : As another combination of decision trees, BoT differs from BaT and RF in using the classification results of previously trained decision trees for the training of the next one. This is achieved by adapting the probabilities of specific training instances to be drawn during the next bootstrap. Consequently, all decision trees must be trained successively[7] .

8) Artificial Neural networks (ANN) : An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (more than a certain threshold), the neuron is activated and emits a signal though the axon. This signal might besent to another synapse, and might activate other neurons.ANN is having many advantages like massive parallelism, distributed representation and computation, learning ability, generalization ability, adaptivity, inherent contextual information processing, fault tolerance, and low energy consumption. ANNs can also be used for classification of BCG signals. According to Xinsheng Yu et.al. a combined wavelet transforms and neural network classifier has more reliable performance[8].

AliMap: Alireza Akhbardeh et al introduced AliMap for pattern classification [15]. This Map tries to eliminate redundant information without losing relevant information incorporated in spatial, time, and frequency domains. This map is able to extract most important information and quantify them using scalar values, mapping from a high dimensional space to one scalar value. It has three factors to decide which information of input data is most important. This transform can be used for automatic pattern classification. The method is insensitive to latency and non-linear disturbance

IV. CONCLUSION

According to these studies accelerometer gives better results than EMFi sensors. The combined methods like wavelet analysis for feature extraction and artificial neural networks for classification has more reliable performance. There are different wavelets including Haar wavelet, Symmlet wavelet, Spline wavelet , Daubechies wavelet can be used for analysis. Multilayer ANN will give desirable classified output. Principal component analysis can be used reduce the dimensionality. Long term analysis of heart using BCG can be used to reduce the death due to the cardiac arrhythmias.

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