Journal of Basic and Applied Engineering Research
Print ISSN: 2350-0077; Online ISSN: 2350-0255; Volume 2, Number 2; January-March, 2015, pp. 153-158

http://www.krishisanskriti.org/jbaer.html

Computation of Bioelectric Signals for Medical Diagnostics: A Review

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Abstract—*Bioelectrical signals are the electric stimulation of living tissue generated by biological processes. It includes the Electrocardiogram (ECG), Electroencephalogram (EEG), Magneto encephalogram (MEG), Galvanic Skin Response (GSR) and Electromyogram (ECG). These bioelectric signals are generated from heart, brain, skin and muscle, respectively and are used for diagnosing person's state of health. The advancement in computing technology provides us an opportunity to analyze the bioelectrical signal automatically and detect any arrhythmia found in a particular organ or tissue. This paper presents a review of computational procedures employed for automatic analysis of bioelectrical signals for medical diagnosis. The ECG signals are mainly used for arrhythmia detection. Automatic analysis of the ECG and its interpretation can detect different heart arrhythmias like normal sinus rhythm, bundle branch block, sinus syndrome, ventricular and atrial fibrillations. The EEG is found to be an important attribute for autism, epilepsy and alzheimer detections. The MEG signals are also used as a diagnostic tool for Alzheimer detection. The GSR is primarily used to examine the function of nervous system. Now a days, wireless GSR healthcare system is used for the stress management. The EMG is proved as a tool for rehabilitation and sports biomechanics. It is used to detect myopathy which is a kind of muscle disease. We critically evaluate different computation methods that are developed in the past for automatic analysis of bioelectrical signals and validate their effectiveness to use as an expert for diagnosing the arrhythmias..*

1. INTRODUCTION

The signals that are generated through the summation of electrical potential differences across a specialized tissue are called bioelectrical signals. The Bioelectric signals includes electrocardiogram (ECG), electroencephalogram (EEG), Magnetoencephalogram (MEG), Galvanic Skin Response (GSR) and Electromyogram (EMG). These bioelectric signals are used for medical diagnosis of a person's state of health. In the modern world, cardiovascular disease (CVD) is one of the most common causes of death, being responsible for approximately 30% of deaths worldwide, and nearly 40% of deaths in developed countries. Although the CVD rate is declining in high-income countries, the rate is on constant increase in every other part of the world [1]. In India the government data says that the prevalence of heart failures are due to coronary heart disease such as hypertension, obesity, diabetes and rheumatic heart disease. The number of people affected by these heart diseases ranges in between 1.3 million to 4.6 million, which reflects the annual incidence of 4,91,600 to 1.8 million. A report on cardiovascular disease scenario in India is prepared by the Associated Chambers of Commerce and Industry of India (ASSOCHAM). According to the report the leading cause of heart patients in India is its economic growth and urbanization. Large sections of the people are not

having a healthy lifestyle with decreasing physical activity. At the same time there is an increase in stress. The large consumption of saturated fats and tobacco are also adding to the heart disease patients.

The analysis of the ECG is widely in use for the diagnosis of many cardiac diseases. Diseases can be classified as action potential such as arrhythmia disease and the other one is excitation pattern. Most of the clinically useful information from ECG is found in the intervals and amplitudes defined by its significant points or the characteristic wave peaks and boundaries. The development of accurate and robust methods for automatic ECG wave delineation is a subject of major importance, especially for the analysis of long recordings. As a matter of fact, QRS detection is necessary to determine the heart rate, and as a reference to beat alignment. ECG wave delineation exhibits fundamental features such as amplitudes and intervals which are used in subsequent automatic analysis. [2]

Through this paper, we convey information regarding the characteristics, strengths and limitations of all the bioelectrical signals which can be used for medical applications. This paper presents an evaluation of bioelectrical signals for medical diagnosis.

We critically evaluate the performance of these signals as medical diagnosis on different datasets and test conditions that have been used by the researchers. The challenges involved in using these bioelectrical signals as medical diagnosis are reviewed. The prime challenge involved in using these bioelectrical signals for medical diagnosis applications is the signal acquisition variations and the lack of standardization of signal properties. The basics of different bioelectric signals and the factors supporting to use them in medical diagnosis are given in section 2. There is also a representation of the review consisting of the existing methods that explore the feasibility of the bioelectric signals in medical diagnosis. The hurdles and challenges that came along, while implementing bioelectric signals to diagnose diseases across a wide range of circumstances and some of the encouraging directions of future research for successful utilization of the bioelectric signals are presented in section 3.

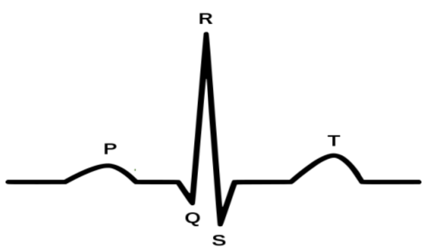

Fig. 1: ECG waveform

2. BIOELECTRICAL SIGNALS IN MEDICAL DIAGNOSIS

2.1 ECG in Medical Diagnosis

The electrical activity which is produced across the heart over a fixed interval of time generates recordings termed as Electrocardiogram (ECG). The electrical signal generated over the heart is the result of electrical conduction system which is due to the effect of polarization and depolarization across the cardiac tissue. The electrical conduction gives rise to electrical impulses. These impulses can be represented in the form of waves. These waves are categorized as P wave, QRS complex and T wave as shown in Fig. 1.

. Zhu *et al.* [3] presents a new approach (IEMMC) maximum margin clustering method with immune evolution to automatically diagnose ECG arrhythmias. The entire process includes three stages. They are signal processing, feature extraction, and the use of proposed IEMMC algorithm for the clustering of ECG arrhythmias. First, the raw ECG signals were captured and processed through an adaptive ECG filter. The filter used was based on wavelet transforms. The extracted features from ECG signals were processed by the proposed IEMMC algorithm to cluster the different categories of arrhythmias. To compare the effectiveness of IEMMC algorithm three different types of performance evaluation metrics were used. They are sensitivity, specificity, and accuracy. The comparison shows that the IEMMC algorithm reflects better performance than K-means and iterSVR algorithms. The algorithm reflects better performance in domains such as in clustering result, global search ability and convergence ability.

Nasiri *et al.* [4] presents a new approach to classify cardiac arrhythmia disease. They employed Support Vector Machine (SVM) and the Genetic Algorithm on MIT-BIH dataset to recognize different classes of arrhythmias. They extracted twenty two features from ECG waveform. These features were obtained semi- automatically from the time-voltage of P wave, QRS Complex and T wave. The major emphasis was laid on correctly identifying features from ECG waveform as certain features may also act as noises and can negatively affect the outcome. The required feature selection may improve the quality of classification. However, In the absence of efficient deterministic feature selection algorithm, meta-heuristic approaches are considered for feature reduction. Genetic algorithm is used to enhance the generalization performance of SVM classifier. Through the above mentioned technique four different types of arrhythmias were detected with a precision rate of 93%.

Bulusu *et al.* [5] proposed a method to diagnose myocardial ischemia and to classify major cardiac arrhythmia. A two-fold contribution for ECG signal analysis for arrhythmia detection was presented. The purpose was done by automated classification of ST-segment deviations and transient ST episodes. The approach was based on the application of ECG signal processing. To classify heart beat segments an improved morphological feature vector was designed by supervised learning which includes ST-segment information using the support vector machine. Firstly, they delineate the ST-segment in ECG waveform, which is required in ischemia detection. Secondly, they implemented a Support Vector Machine for classifying heart beats segments into six major categories. The ST-segment analyzer throws an accuracy rate of 98.57% in ST-recognition and 97.34% in ST-deviation measurement.

The system was tested for classifying six major groups, i.e. Normal, Ventricular, Atrial, Fusion, Right Bundle and Left Bundle Branch Block beats on the European ST-T Database and on MIT-BIH Arrhythmia Database and yielded an accuracy of 93.33% and 96.35% respectively.

Kannathal N *et al.* [6] proposed a novel classifier based on Adaptive Neuro-Fuzzy (ANF). The classifier acts as a diagnostic tool for a physician to diagnose patients with different heart diseases. The database for classification purpose was taken from MIT-BIH arrhythmia database. Ten classes of arrhythmia classification were chosen. This includes Normal Sinus Rhythm (NSR), Left Bundle Branch Block (LBBB), Preventricular Contraction (PVC), Atrial Fibrillation (AF), Ventricular Fibrillation (VF), Complete Heart Block (CHB), Ischemic/Dilated Cardiomyopathy, Sick Sinus Syndrome (SSS), Paced Rhythm (PR) and Congestive Heart Failure (CHF). Three parameters were derived which were used as an effective inputs for the classification of heart abnormalities. These three parameters act as an input for the proposed ANF classifier. The parameters were Largest Lyapunov Exponent (LLE), Spectral Entropy (SE) and Poincare plot geometry (SD1/SD2). These parameters were used to extract the nonlinear features from the ECG waveform. It was shown that the proposed classifier achieved the classification accuracy in between 85% -100%. LLE gives the measure of predictability by quantifying the sensitivity of the signals to initial conditions. The spectral complexity of a time series signal was quantified by SE. A standard deviation parameter SD1 related to the fast beat-to-beat variability and SD2 related to the longer-term variability of R-R wave. Ozbaya *et al.* [7] presents a classification algorithm for early diagnosis of 10 different arrhythmias. They presents a comparative study for the initial processing of ECG waveform with the help of multi-layered perceptron model (MLP) along with back-propagation training algorithm. Fuzzy clustering NN architechture (FCNN) was given for early diagnosis of arrhythmia patients. The testing was done with the experimental records of 92 patients which include 40 males and 52 females. The records were taken from MIT-BIH ECG database. An experimental result shows that the learning of the proposed algorithm is far better and faster than the ordinary MLP architecture with relatively few signal features. With reference to time taken for training period FCNN takes 60% of the time as required by MLP architecture. The results were more reliable with FCNN. The advantage was due to the decreasing number of segments by clustering the similar segments within the training data with fuzzy c-means clustering. The performance of FCNN can further be increased by increasing the number of beats during the training period.

Sarkaleh *et al.* [8] proposed an expert system to automatically detect and classify ECG arrhythmia. The system consists of two phases. The training and testing of neural network based classifier was achieved by ECG recordings from publically available database MIT-BIH arrhythmias database. The first phase includes the processing and extraction of feature set from ECG waveform. This was done by employing moving average filter to eliminate the baseline noise from the ECG signal. The Discrete wavelet transform was applied on the filtered signals to extract certain features from the wavelet coefficient. In the second phase the classification process was performed using Multi-Layer Perceptron (MLP) neural network on the extracted features. Through this technique two different types of arrhythmias were detected. They achieved the classification accuracy of algorithm as 96.5%.

Gothwal *et al.* [9] studied Cardiac arrhythmias as a condition of abnormal electrical activity in the heart, identified as a threat to humans. They came up with a method to analyze ECG signals and classify the heart beats according to different arrhythmias after the extraction of features. Data was obtained from 40 records of the MIT-BIH arrhythmia database. Cardiac arrhythmias such as Tachycardia, Bradycardia, Supraventricular Tachycardia, Incomplete Bundle Branch Block, Bundle Branch Block, and Ventricular Tachycardia were diagnosed. Learning of neural network was done from a set of twenty records which were manually classified using MIT-BIH Arrhythmia The peaks in the ECG waveform were identified using Fast Fourier transforms (FFT) and then applied Neural Networks for the identification of the diseases. The network was trained by utilizing the Levenberg Marquardt Back-Propagation algorithm. The method was proved to yield better results than the previously proposed methods in terms of efficiency.

Bermudez *et al.* [10] addressed the automatic detection of epileptic events by the fusion of electroencephalo- graphic and electrocardiographic time-series. The process worked by coupling the brain and heart systems together during the temporal lobe epileptic events. A central autonomic network was used for the coupling process. It was proved that the biomedical data combine of simultaneously recorded EEG and ECG time series had the capability to detect genuine epileptic events and to dramatically reduce false positives.

2.2 EEG in Medical Diagnosis

EEG is the recording that is the result of electrical activity across the scalp. Our brain consists of neurons and these neurons produce an ionic current which flows from one neuron to other neuron. The current flowing from neuron to neuron creates a potential difference and measure voltage fluctuations. These voltage fluctuations are recorded through the electrodes placed over the scalp usually in between the time period of 20-40 minutes.

Kamel *et al.* [11] conducted a study in which EEG was found to be an attribute for autism detection. Diagnosis of autism is one of the difficult problems faced by researchers. They performed Autism diagnosis using Fisher Linear Discriminant (FLD) Analysis. Multivariate analysis of all the channels via the concatenated signals were used along with the study of different preprocessing techniques, different ensemble averages and different feature extraction techniques. The average correct rates were (90%). They used raw data features and Fast Fourier Transform (FFT) features. The best mean and the lower standard deviation of both raw and FFT features was provided by the Windsor Filtered Data. Over all, FFT features have a better correct rate of 88.14% and lower standard deviation of 0.0404 than raw features.

Song [12] proposed that EEG can be used for epilepsy detection. Epilepsy is so common a neurological disorder that it encompasses a large toll wherein approximately one in every 100 people worldwide are suffering from it. The electroencephalogram (EEG) is a common and widely used source conveying information that is capable to perform the functions of monitoring, diagnosis and management of neurological disorders related to epilepsy. Large amounts of data were produced by EEG monitoring devices. The analysis through visual inspection of long recordings of EEG in order to find traces of epilepsy is remotely feasible. the researchers have been targeting automated detection of epilepsy. The reviews of epileptic seizure detection have been published umpteen times but none of them specifically contained developments of automatic medical support systems utilized for EEG-based epileptic seizure detection.

Elgendi *et al.* [13] gives an evidence of the fact that

Alzheimer patients (AD) often have EEG of an abnormal power spectrum. To enhance the diagnosis of AD through EEG signals, they performed a frequency band analysis of AD and EEG signals. The distinguishing characteristic between AD patients and healthy control subjects was the relative power in different EEG frequency bands. Systematic testing was conducted for different frequency bands between 4Hz and 30Hz, except for the traditional frequency bands such as theta band (4Hz-8Hz). Statistical tests (Mann Whitney U test) were performed which highlights the discrepancies of the resulting spectral features. Moreover, linear discriminant analysis (LDA) was conducted with those spectral features. The optimized frequency ranges (4Hz-7Hz,

8Hz-15Hz, 19Hz-24Hz) outdo the traditional frequency bands (4Hz-8Hz, 8Hz-12Hz, 12Hz-30Hz) when it comes to their performance. The ideal frequency range for detecting AD is in between 4Hz-7Hz, which shares common features with the classical theta band. To make the classification devoid of any error, leave-one-out cross validation was taken up to enhance the features of the frequency bands. The optimized frequency bands may mark an improvement in the existing EEG based diagnostic tools for AD. The recently introduced approach tests larger AD datasets for their verifiability on effectiveness.

2.3 MEG in Medical Diagnosis

The neroimaging procedure of mapping brain activity

through magnetic fields generated by electrical currents prevailing normally in the brain by the use of sensitive magnetometers is termed as Magnetoencephalography (MEG).

Carlos *et al.* [14] diagnose Alzheimer disease (AD) through MEG signals. However, they proceeded with the manipulation of magnetoencephalography (MEG) background activity in Alzheimer disease (AD) patients using cross approximate entropy (Cross-ApEn). Cross-ApEn is a nonlinear measure of asynchrony between time series. A 148-channel whole-head magnetometer in 12 AD patients and 12 age-matched control subjects was operated and recorded for 5 minutes. There was evidently higher synchronization between MEG signals from AD patients as against control subjects. Using receiver operating characteristic (ROC) curves with a leave-one-out cross-validation procedure, the ability of Cross-ApEn to differentiate between these two groups was also assessed. An accuracy of 70.83% (66.67% sensitivity, 75% specificity) and a value of area under the ROC curve of 0.83was obtained. These results were evident of disconnection problems in AD. Hence, the usefulness of Cross-ApEn to detect the brain dysfunction in AD was inferred by them.

Mohseni *et al.* [15] illustrated a new approach for the integration of multichannel signals. The signals that are generated from the sensors that are used in Magnetoencephalography are combined together. They presume that the lead-fields have multiplicative errors. These multiplicative errors may leads to an under determined problem. As a result, they imposed two constraints that results in closed from solutions. The constraints specify are (a) one set of sensors is error free and (b) the norm of the multiplicative error is bounded. These presumptions were made to detect errors and are used in the linearly constraint minimum variance (LCMV) spatial filter for optimization purpose. This approach can be undertaken for multimodal integration of other multichannel signals such as MEG and EEG signals, despite their focus on the fusion of MEG sensors.

2.4 GSR in Medical Diagnosis

In today’s world, the medical field has received immense contribution from Electrocardiography response (ECG) and Electroencephalography response (EEG). Galvanic skin response (GSR) is heading towards becoming a reliable medical diagnosis with increasing growth in the field of medicine

Huang *et al.* [16] explained the principle of wireless GSR healthcare system in their research. GSR as the performing factor is utilized in the design and implementation of a novel medical healthcare system. Wireless RF module PTR8000 controls the movement of the measurement data between the primary stage and the subordinate stage, as adopted by the system. The subordinate stage collects the GSR signal and converts analog signal into a digital signal, then sends it away. the primary stage receives the data, then stores and displays them. The system proves to be reliable and highly useful in the healthcare field according to the experiments conducted.

Kurniawan *et al.* [17] took up the ever-increasing problem of stress management which has been an important issue demanding serious attention. Research communities these days are focusing on the wide range of potential problems caused by chronic stress. They are looking into the recent developments of technologies providing non-intrusive ways of collecting continuously objective measurements to monitor a person’s stress level. Galvanic Skin Response (GSR) and speech signals, according to recent experiments conducted, are two tabs that can help assess the stress level. There is investigation as to how the information contained in GSR and/or speech of a person can automatically determine periods of acute stress for a person.

2.5 EMG in Medical Diagnosis

Whenever a muscle is activated, an EMG signal is produced. An activation of muscle can be of any form such as variation in muscle fibre pattern, changes in blood flow, neural activity, skin conductivity, shape and size of muscle and body fat.

Kugler *et al.* [18] talked about surface Electromy- ography (EMG) that serves as an important tool for medical diagnosis, rehabilitation and sports biomechanics. Although it has the power to record data under laboratory conditions, dynamic movements have also been recorded successfully using mobile wearable sensors. This has led to feedback applications which require real-time processing of the EMG data on mobile devices. The mobile EMG analysis structure contains a wearable recording device, a wireless mobile sensor framework and a real-time biosignal analysis library.

Bue *et al.* [19] proposed a method to detect and measure the severity of myopathy. Myopathy is a muscle disease and can be evaluated by electrical action potentials produced by humans. The shape and frequency of these electrical action potentials are captured in EMG measurements. EMG measurements are different for different subjects relative to different muscles and also according to session specific characteristics such as muscle fatigue and degree of contraction. A fixed-duration of (0.5Sec-2sec) is taken for frequency-domain samples of diagnostic regions in EMG signals which are measured at full muscle contraction. The proposed technique can automatically detect the presence of myopathy with an accuracy of 90%. The methodology proves to be more effective and efficient than motor unit action potential (MUAP) waveforms.

3. DISCUSSION AND CONCLUSION

Through this paper, we gather information about the exploration of the effectiveness of all the bioelectrical signals such as ECG, EEG, MEG, GSR, EMG for medical diagnosis. Reports have been presented regarding the research challenges involving bioelectric signals in the domain of medical diagnosis. Incorporating the bioelectric signals to be used for medical diagnosis opens the door to several advantages. The physiological features of bioelectric signals can only be acquired of the person who stands alive.

We would make the utmost of our efforts to analyze the parameter, the success of which paves the way for hopeful detection of Heart disease. Every bio-signal is an integration of action potential and excitation patterns. The paper helps in grasping the profound concept of signal processing and using them to understand and diagnosing various heart abnormalities. Effective testing shall be conducted of the methods used to implement bioelectric signals over normal healthy subjects for medical diagnosis.

We have reviewed and evaluate the work of different authors and found the limitations of using ECG in medical diagnosis. According to them the extracted ECG pattern may be influenced through different artifacts of motion. The artifact generated is induced by different body movement activity. It includes sitting, walking, moving, running, climbing and other movements of arms etc. Thus, to eliminate these artifacts it is required to study the impact of these artifacts in the ECG signals. Hence, a better filtering algorithm can be formulated by studying these artifacts.

There biggest challenge in using EEG as medical diagnosis is the appropriate placement of scalp electrodes. Placement of electrode is bit a tougher task which may hinders the data acquisition process. Placements of electrodes are affected by different body movements such as eye blinking, muscle activation etc. Thus, placement of scalp electrodes in a best possible manner needs to be researched.

A very limited research has been done to use GSR and EMG signals in the field of medical diagnosis. The future improvements of EMG includes standardization of better electrode position, better feature extraction from EMG signals and Refining the parameters used to maximize usability and performance.

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