Deep learning Scheme for Acquisition Errors Elimination in ECG Data by the Empirical Mode Values of Independent Components Associated Decomposition

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Abstract. A proposed methods seeks to improve the processing of Electrocardiogram signals with the intent of reducing the impacts of power-line interference and magnetic-field defects that commonly result in uncertainties of medical diagnosis. The initial step of our proposed approach involves decomposition of Electrocardiogram signals through Empirical Mode Decomposition to identify the resolution of the signals into intrinsic mode functions to identify the underlying patterns. The subsequent step involves application of Independent Component Analysis (ICA) through Independent Component Generation step thru the intent of identifying the independent components of the signal to facilitate easier interpretation of the signals to distinguish signal components from noise. After rigorous noise elimination, our proposed approach applies the inverse of ICA and Empirical Mode Decomposition to generate an improved version of the signals with increased realism due to the elimination of noise that may still exist.

Keywords: ECG, EEG, ICA, Artificial Intelligence and Empirical Mode of Decomposition.

1 Introduction

The cycle of change in the electrical action potential, characteristic of heart activity, is measured through the use of surface electrodes placed directly on heart. Voltage difference measured using the electrodes cycles as the encounter potentials spread from the atrium through ventricles, indicating heart electrical dynamics. The placement of the recording electrodes allows for varied insights of the electrical activities, as a basic way of deriving a complete understanding of heart activities[1]
This is fact that the body is a good conductor of electricity, enhanced by flow of ions in tissue fluid between potential differences, allows for the transfer of these potential

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differences that have been developed at the heart to the surface of the body. The transfer of these further potential differences allows for the capturing of electrical activity using surface electrodes placed on skin; this results in the development or production of an electrocardiogram, also referred to as ECG or EKG. In recording an ECG, two kinds of electrodes have been used, including bipolar limb leads and unipolar leads. Under bipolar limb leads, there is lead I, which consists of right arm to left arm, lead II from right arm to left leg, and lead III from the left arm to the left leg. There are also unipolar leads such as AVR, AVL, and AVF, recording the voltage between the exploratory electrode placed on the body & the ground electrode[2]. In addition, unipolar chest leads, ranging from one to six, can be used to gather more information from various points along the thorax. Here are twelve different leads within the electrocardiogram, each providing a different view of the heart's electric functions. Variety in the electrocardiogram is very crucial since heart problems can only be fully observed from various leads, thereby explaining the significance of viewing the heart from various leads[3] Therefore, in a nutshell, the application of multiple leads in the recording process of the ECG is useful for the diagnosis and treatment of the electrical activity functions performed by human heart through application of deep learning[4]

Each cardiac cycle consists of the production of three waves related to the ECG signal, named P, QRS, and T waves. An essential aspect to clarify, for those who are not acquainted with the basics of physiology related to the heart, is the fact that these waves are not action potentials but the mapping of differences in potentials along the heart surface, produced by many action potentials[5]. For instance, the ECG wave turns upwards owing to the potential difference resulting from the transmission of depolarization through the atria. However, highest potential difference between the non-stimulated & depolarized regions is represented by peak of the wave and happens around the mid-level of the atria. Additionally, the ECG wave turns to baseline once the depolarization reaches the entire regions in the atria to indicate that the atria regain their polarity. In fact, the entire wave is referred to as P wave since it represents depolarization of the atria. In same way, once the impulse reaches the ventricles, the ECG wave turns sharply upwards to the baseline once the ventricles depolarize. In fact, the entire wave is referred to as the QRS wave since it illustrates ventricular depolarization[6].

2 Related Work

Problem of discriminating amongst actual and actual EEG activities is generally raised by Arjon Turnip and Dwi Esti Kusumandari (2015), [7] in the process of examining the EEG activities due to various extrinsic factors. The EEG activities obtained may be affected by the distortions. To remove the distortion artifacts, an adaptive recursive least squares method for extraction in combination with wavelet and band pass filter is suggested in this research for preprocessing. The proposed method aims to recursively and adaptively generate, in a manner that maximizes information retained in original variables, a very small set of decorrelated linear arrangements of a set of random variables having zero means. The actual EEG activities of eight subjects were employed for testing the proposed method. The experiment proves that all subjects can successfully remove artifacts by using proposed method.

Characteristic points of Fetal Heart Rate (fHR) and signal shape in the course of pregnancy are only a few of possible information that can be obtained from abdominal fetal Electrocardiograms (fECGs). In this paper, Radana Kahankova et al.,(2017)[8] exhibited their results concerning utilization & evaluation of two non-adaptive methods for signal processing-suitable for fECG signal extraction: PCA and ICA Systems. The efficiency of the methods we implemented was evaluated based on the fHR (measured in beats per minute, BPM) and the SNR, both extracted from fECG signals. Our results indicate that both methods give excellent performance in estimating fHR in cases when the SNR is sufficiently high. Furthermore, we found that ICA Method gives a lower variance in the estimation of fHR than PCA technique.

Among major grounds of death, most cases heart disease tops the list. So, in an effort to reverse the growing rates of deaths, the diagnosis of heart disorders needs to be done earlier. Electrocardiogram (ECG) classification is the widely used diagnosis process for various heart disorders, such as irregular heartbeats, referred to as arrhythmias. However, the identification of the features of the abnormal ECG signals will be very difficult, though not possible, owing to non-linear characteristics of the abnormal signals. Additionally, validation of aforementioned abnormal ECG signals will require a considerable amount of time. Mohamed Hammad et al. (2019)[9], developed a fast and accurate classifier that, using the single-lead ECG signal, can effectively classify the normal and the abnormal ECG signals better than the various existing famous classifiers. Mohamed Hammad et al. stated that the classifier replicates the cardiologist's diagnosis. Initially, the main features of the various heart signals are obtained, along with the removal of the noise content within the signals using an accurate approach.

Then, they modeled the characteristics of the ECG signals and based on those characteristics, their built the recommended classifier, To classify ECG signals & compare those results by ones obtained by suggested classifier, we employed four Support Vector Machine (SVM) classifiers, two Neural Network(NN) classifiers, and a K-Nearest Neighbor (KNN) classifier. A proposed technique employs all 13 features extracted from each ECG signal and fed into the other classifiers. Our technique is tested by using every record in the MIT-BIH arrhythmia database. Based on the experimental data, suggested classifier betters other classifiers & produces highest average classification accuracy: 99%. Thus, our algorithm stands the chance of application in clinical situations [10].

The bio-signal or the signal from the patient is used to determine the status of the patient. Then, such vital bio-signal is the electrocardiogram signal, which provides the efficiency of heartbeat. Arrhythmia condition is the name given to the irregularity in the ECG signal. It is an indication of the crashing of heart. Long-term analysis with the help of computer-aided diagnosis (CADiag) is preferred due to the complications involved, such as the tendency of being misled into incorrect diagnosis and the absence of expertise. Various CADiag techniques are present. Each has its positives and negatives in the diagnosis of arrhythmias. Depending on the type of CADiag used, the strategies involved in the detection of the Arrhythmia condition caused due to CADiag are explained in the work done by Dinakara Rao et al. (2022) [10]. Various approaches are explained in the paper. Various approaches to the detection of Arrhythmia are compared in this article, depending upon the efficiency of process and its aptness to be implemented in a wearable device[11].

Classification of the ECG signal is required for diagnosis of cardiovascular diseases. Recently, low-cost wearable devices have advanced to such an extent that the classification of ECG signals has emerged as a sensible approach in practical applications for the diagnosis of cardiac arrhythmias in everyday life. Yuwei Zhang et al. (2020) [12] proposed a simple way of classifying five kinds of cardiac arrhythmias:

Normal Beat (N), Atrial Premature Contraction (A), Premature Ventricular Contraction (V), Left Bundle Branch Block Beat (L), and Right Bundle Branch Block Beat (R)[12]. Shannon entropy & frequency analysis both provide correct arithmetical property to application. Feature selection is performed by the use of the information gain technique, and it has been observed that the best ten most effective features are also able to provide performance metrics similar to the one given by the process of the entire dataset of all features. The features are further used for the classification purpose of the Random Forest classifier, K-Nearest Neighbor classifier, and J48 classifier. The classification performance is checked by the use of ten-fold cross-validation to confirm efficacy of the proposed work. The proposed Random Forest classifier has surpassed numerous existing techniques related to the automatic classification of cardiac arrhythmia with maximum sensitivity of 98.1%, specificity of 99.5%, precision of 98.1%, and accuracy of 98.08%.

3 Methodology

One of the fascinating research issues to be addressed in field of biomedical signal processing is recovery of ECG signal at a high resolution from a noisy signal. At the current stage of technological development, the recovery of ECG signal from a signal with a low SNR is the highest achievement in the use of deep learning in the non-invasive recovery of the fetal ECG signal from an array of electrodes positioned on abdomen[13].

However, some recent works have been conducted for the false ECG signal generation. In terms of the physiological mechanism for the ECG signal, the false ECG model should take into account the PQRST waveform and the time intervals of the RR waves. The previous work[14] presented a synthetic model by integrating waveform & pulse time of ECG signal hooked on a nonlinear dynamic model. It's model can be regarded as being appropriate for a wide spectrum of normal and pathological ECG signals due to its flexibility & ease of use. This idea can also be implemented for ECG filtering techniques using deep learning techniques. At the same time, the nonlinear counterparts for the conventional machine learning techniques are demanded by the nonlinear dynamic model[15].

They designed an EKF for the extraction of noisy ECG data, employing the dynamic model explained above. The ECG data model has been advanced for the proposed research in order to meet the set requirements in the filtering process. In addition, the process of choosing the parameters in the EKF model has been automated to have the capability of adapting the strategy with different normal and abnormal ECG data. Obtained analysis shows that the proposed approach is capable of completely following the ECG signal pattern, regardless of noisy signals where the actual ECG signal is well obscured in the noises. ECG signals are very important in diagnosis of cardiovascular diseases, pulmonary diseases, and sudden cardiac arrest, among other diseases related to heart. ECG signals are produced as a result of heartbeat caused by the nerve impulse. The frequency of signals is 0.05-100 Hz. The voltage drop, which is 0.0001-0.003 volts, is accumulated through the flow of current in the body[16].

The ECG signal is normally recorded on the surface of the skin and processed in such a way as to yield crucial details about the electrical activities performed by the heart. The path represented in an ECG signal waveform includes P, QRS, and T waves. Potential of the signal derived from human body is modest. This makes it quite difficult to determine the variance of the signal. Thus, it becomes essential that the signal be subjected to the necessary amplification in order to yield any crucial details concerning cardiac ailments.

The observation of the physiological activities of an organism through its tissues and organs, protein sequences, heart signals, or brain signals falls within the biological signals. Biomedical signals can be generated through the observation of these signals through electrodes that detect the variation of electric potential, which results from such activities. Different signals relate to distinct functions of the physiology of an individual, depending on its characteristics. It is always possible to distinguish any disorder through the observation of these signals against predetermined standards. Over the years, through continuous observation, one-dimensional time-series signals called physiological signals have been measured. An example of such an anomaly includes cardiac arrhythmia, which refers to any variation from the normal rhythm of the heart. Cardiac arrhythmias include irregular muscle spasms of the heart muscle, which may have dangerous implications of damage to the heart or sudden death. It is always practical to determine such arrhythmias through a precise diagnosis of the electric activities of the heart through an electrocardiogram.

The development of the application's model entails a number of important steps. Firstly, there is pre-processing of the ECG signal for improvement in quality. This is achieved through the use of Pan-Tompkins and Hamilton-Tompkin's algorithms, tailored to meet the specific application requirement for signal pre-processing and extraction of features, including the extraction of the QRS complex. The algorithms applied in this project are renowned for their success in this exercise.

Following the pre-processing phase, the process involved is the extraction of the features to detect the corresponding features present in the ECG signal. This is the key activity involved in the extraction of the features to be applied in the classification. These features are then grouped according to the respective groups through the application of the Backpropagation Neural Network (BPNN). The training of the BPNN is conducted through the application of the Levenberg-Marquardt (LM) algorithm.

The proposed application model will be developed utilizing MATLAB software together with the MIT-BIH data base, which is one of most used data bases for reference ECG signals. It will be able to process digitally recorded ECG signals.

A block diagram is shown in Figure 1 for an ECG beat classifier designed in the system. This depicts the flow of data as well as the processes in the model. Descriptions and details about the model are provided in the figure.

In short, this methodology will be able to create an effective beat classification model in an electrocardiogram signal classification process. This is an important aspect in medical applications employed in the advancement of the use of deep learning.

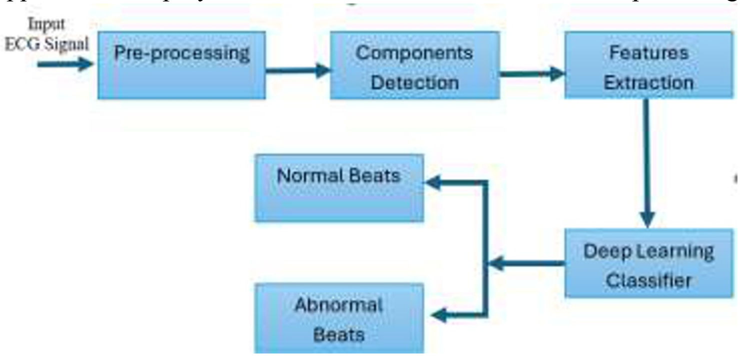

Figure 1: shows the ECG beat classifier's block diagram.

4 Result and Discussion

After completing the ICA decomposition, the algorithm has all the Independent Component Analysis components in one window. In addition has the kurtosis values of all the ICA components created, which are listed under.

kurtosis of ICA components = kicina

(1) 2.4905	(2) 3.4545	(3) 2.4358	(4) 2.4409
(5) 2.7921	(6) 2.6080	(7) 1.9007	(8) 2.9257
(9) 2.7919	(10) 2.7599	(11) 2.7069	(12) 3.2093

However, for case of the representative data, the sample moments for random samples, up to a point, will be somewhat different from the moments of the distribution. In the above-mentioned value, the kurtosis of the majority of the sample values is 2.4 to 2.7, but the 2nd , 7th , and 12th kurtosis distribution are different, & the 7th ICA component kurtosis value does not belong to the rest. Hence, for the 7th ICA component, the reverse ICA is again applied to reconstruct the EMD components. Then, the reconstructed EMD components are again reconstructed into the ECG signal. Actual, noisy, and noise-cancelled signals will be observed in the Figure 2.

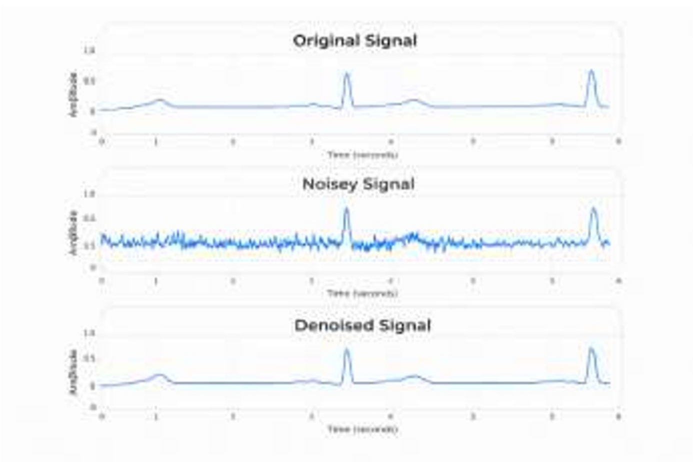

Figure 2: Original ECG waveform, both noisy and denoised

As explained above, the usage of the denoising phenomenon using deep learning in different cycles of the ECG and the calculation of mean square error in concerning the original and noisy signal as well as the original and the denoised signal is explained below. The results are given one by one.

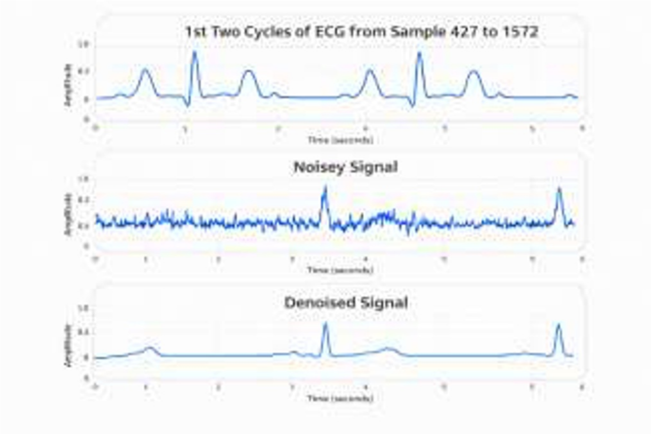

Figure 3: ECG data denoising outcome for the first cycle

MSE original with respect to noisy = 2.7082 x107
MSE original with respect to denoised = 1.6605x107
Remark: Denoising reduces error.

5 Conclusion

In our research, we are specifically trying to solve the problems caused by distortions in the commonly practiced amplitude measures in the ECG. Using the results obtained through the analysis of ECG amplitude, we construct novel sets using the temporal averages of the ECG segments, R peaks, or ST segment amplitudes. The purpose is to improve the diagnostic process with the help of an system that incorporates both Independent Component Analysis (ICA) and Empirical Mode Decomposition (EMD) techniques with the intention of reducing the errors in the database of the ECG. The combination of the concepts of ICA and EMD decomposition methods provides a significant way for the reduction of errors in ECG signals using deep learning methods. In fact, ICA is largely used in processing systems for analysis in different applications. In ECG analysis, in particular, it has proved very useful in methods such as the analysis of patients diagnosed with atrial fibrillation, analysis for heart rate variability, analysis for parameterized ECG, analysis for classification using deep learning, among others. Through effective use of these methods, our proposed approach aims at enhancing the diagnostic process by reducing distortions in ECG amplitudes for easy analysis of cardiac elements.

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