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Paper Authors
Alok Singh Gahlot

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Computational Modeling of Heart for ECG Interpretation: A Review

Alok Singh Gahlot[1]
[1]Assistant Professor ,MBM Engineering College, J. N. Vyas University, Jodhpur 342001, Rajasthan, India

***Abstract*:** The electrophysiology of the heart has made considerable strides in computer modelling. From the ion channels, through the distribution of a depolarization wave on a realistic geometry of the human heart, up to the potentials on the body surface and the ECG, a healthy heart may be recreated. Modeling cardiac disorders is a growing field of study. Using simulated depolarization and repolarization waves, this article summarizes the advances made in computing and analyzing the associated electrocardiogram (ECG). We first go through modelling of a healthy heart's P-wave, QRS complex, and T-wave. The modelling and corresponding ECGs of a number of significant disorders and arrhythmias are then identified, including ischemia and infarction, ectopic beats and extrasystoles, ventricular tachycardia, bundle branch blocks, atrial tachycardia, flutter and fibrillation, genetic disorders and channelopathies, electrolyte imbalance, and drug-induced changes. Lastly, we discuss how computer modelling may affect how an ECG is interpreted. Understanding the relationship between ECG characteristics and the underlying heart state and illness can be improved through computer modelling. It may open the door for a quantitative examination of the ECG and aid the cardiologist in pinpointing events or sick regions without invasive procedures.This study shows how to use a Genetic Algorithm (GA) to effectively identify and separate ECG wave components including P-waves, QRS-complexes, and T-waves in multi-channel ECG data. In order to provide some foundation for its use for component wave identification, the fundamental theory of GA is presented. There is a lot of promise in strengthening the connection between the ECG and heart computer modelling

Keywords: Computer Modeling, electrocardiogram ,ECG ,cardiac disease , Genetic Algorithm(GA)

1 INTRODUCTION

The impact of digital signal processing techniques promoted revolutionary advances in many fields of application e.g. biomedical engineering, speech communication, data communication, nuclear science and many others. Electrocardiogram (ECG) is one of the most important electrical signals in the field of medical science which has a great need to be processed before further analysis. Abnormalities of the heart can be detected using electrocardiograms (ECGs) that record the electrical activity of the heart. Cardiac diseases occur when disturbances are caused in the normal electrical events related to the basic process of automaticity, conduction and triggering mechanisms of the heart. ECG interpretation is a very important task performed in Coronary Care Units (CCUs) and ambulatory monitoring systems. If not well diagnosed in time, they represent a serious threat to the patient. Therefore, there is a need for early identification of these abnormal electrical activities of the heart. Both life threatening (e.g. ventricular fibrillation and atrial fibrillation) and not-so-life threatening premature ventricular contraction and atrial premature contraction can be detected with the help of the ECG

This article reviews research aimed at building a bridge between computerized modeling of the electrophysiology of the human heart and the analysis of the electrocardiogram (ECG). Potential applications of computer modeling for better interpretation of the ECG are demonstrated and an outlook for further research is given.The research field of computerized modeling of the electrophysiology of the heart has reached a mature state. The healthy heart can be replicated in a computer model withvarious degrees of detail, starting with the ion channels and ending with the spread of adepolarization wave through the atria and the ventricles. Several diseases have been thefocus of this research but many open questions remain: modeling can only be as good asour basic understanding of the pathologies of the heart.On the other hand, after more than 100 years of ECG interpretation, the clinical knowledge about ECG and what it can tell us about cardiac diseases has reached an expert level. Most often, this knowledge is based on personal experience or empirical studies and only coarse attempts are made to relate a decisive feature in the ECG to its pathologicalorig in inside the heart. The classical heart vector is a valuable tool for understanding thegeneral shape of the ECG, but it is not good enough to follow details of the spatial spread of de- and repolarization.It is astounding that the number of articles where modeling of the heart is extended to the calculation of the ECG and where this is used for better ECG interpretation is limited.

A standard ECG record is an important test for diagnosing all diseases, whether of ventricular or supraventricular origin. An ECG tracing is a series of waves that represent the electrical events of the various chambers and conduction

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pathways within the heart. The electrical activity during the cardiac cycle is characterized by five separate waves of deflections designated as P, Q, R, S and T. A normal ECG is the ordered sequence of depolarization of the myocardial cells, i.e. the sequence of P-wave (atrial myocardial depolarization) and QRS-wave (ventricular myocardial depolarization) generation, at a regular rate of 60-100 beats per minute. When this sequence is disturbed, abnormal patterns in ECG occur. Analysis to diagnose diseases involves the accurate detection of P-waves and QRS-complexes with respect to time, with respect to each other and with respect to space.

Computerized ECG interpretation to detect diseases (off-line or on-line) is a process of ECG data acquisition, waveform recognition, measurement of wave parameters and classification. A plethora of computer based techniques have been reported to detect the abnormalities of the heart. Different methods for feature detection based on digital signal processing of ECG waveform are available in literature. This chapter, therefore, deals with a discussion on analysis, interpretation and identification of wave complexes like P-wave, T-wave and QRS-complexes etc. A brief introduction of the CSE ECG database and outline of the thesis is also given.

2 REVIEW OF LITERATURE

The ECG tracings depicting arrhythmias were shown, for the first time by Einthoven, in the beginning of the last century, sometime around 1905-06 . However, identification of abnormal rhythm and associated parameters, in a recorded ECG, proved to be a complex task for cardiologists. As the invention of transistor led to the development of commercial computers, researchers working at MIT and Lincoln labs in 1961 used the technology of the time to build a transistorized minicomputer called LINC that served as a very useful computational facility for biomedical applications . ECGs could be acquired from patients directly and displayed on its graphics display. Such developments had a great impact on research workers trying to monitor ECGs and evolve methods of automated rhythm analysis. Also, the discovery of Holter monitoring system in 1961, helped to record long-term ECGs that provided the cardiologists the ECGs, with episodes of randomly occurring rhythm abnormalities and sudden beat change. Around this time period of late 1950s and early 1960s, several attempts were made to perform computerized ECG interpretation to identify arrhythmias and other cardiac disorders.

The pioneering work to accomplish analysis of ECG, by a digital computer, was initiated in 1957 by Pipberger and his co-research worker. Pipberger's group described digital conversion of ECGs for the first time at the American Heart Association's 1959 Scientific Sessions and in Circulation in 1960 . Results from a pilot project designed to demonstrate the feasibility of screening of normal and abnormal ECGs were reported by them in 1961. Stallman and Pipberger in 1961 described a more comprehensive automatic ECG wave detection and measurement program. More and more publications ushering in, during this period, created a revolution in the design and development of computer based ECG analysis systems . Impeccable drive to develop computer based ECG analysis systems, led to the conceptualization of two basic approaches, for computerized interpretation of the ECG by early 1970s:

(i) Decision logic approach based on the IF-THEN rule formalism that is easily followed by a human expert. It is basically a rule based expert system.
(ii) Multivariate statistical pattern recognition method in which ECG interpretation as a pattern classification task is employed where decisions are made on the basis of the theory of probability.

In the last decade, the development has shifted to industry. Computers can assist a cardiologist in the task of ECG monitoring and interpretation. For example in cardiac intensive care units (CICU), ECGs of several patients must be monitored continuously to detect any life-threatening abnormality that may occur. Since cardiologists are unlikely to be available to monitor the ECGs of all the patients round the clock, automated monitors programmed to detect abnormal heart rhythms are needed. Over the past several years, the computerized ECG monitors that provide complete 12-lead diagnostic quality ECG recordings and interpretations have become common. Computerized ECG monitoring and analysis are now carried out with bedside monitors, mobile carts equipped with ECG amplifiers and microcomputers and portable ECG recorders hooked up via telephone networks. State-of-the art systems are based on multiple microcomputers, which run, sophisticated arrhythmia analysis software and are connected to central computer facilities where they share patient record and database. In the past four decades, numerous computer programs have been developed for the automatic interpretation of ECG. However, methods and independent databases to test the reliability of such programs are still scare. Each ECG programs has different principle with respect to analysis, for example, some measure single beats, where as others analyze average beats. Earlier, there were no standards in this field. There were no common definitions of waves, no standards for measurement or diagnostic classification and no uniform terminology for reporting, transmission and processing of data. This has created a situation whereby large differences in results of measurements by different computer programs have hampered the exchange of diagnostic criteria and interpretation results . In addition, more and more

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microcomputer-based interpretative ECG machines are being put on the market without any prior independent validation. In order to overcome some of these problems, a concrete action was initiated by European Community (EC) in June 1980 striving towards 'Common Standards for Quantitative Electrocardiography' (CSE)

The prompt and adequate detection of abnormal cardiac conditions by computer assisted long-term monitoring system depends greatly on the reliability of the implemented automatic ECG analysis technique. Although diagnostic accuracy of computer programs is tending to reach a plateau, there is no doubt that many years hence, it will still be possible to report on recent developments in the programs. In all programs, there is every possibility that the work will always be enhanced, modifications for improvements be made and the new techniques like Genetic Algorithm (GA) be introduced for better results

Table 1. Literature survey of research about modeling of the heart together with the correspondingECG.

Topic	***Modelling Challenge***	***References***
healthy heart—QRS	modeling the Purkinje tree	***[1–9]***
healthy heart—T-wave	modeling heterogeneity of repo- larization	***[10–13]***
healthy heart—P-wave	modeling sinus node excitation and pathways from right to left atrium, anatomical variability	***[14–22]***
ischemia and infarction	modeling the effect of hyperkalemia, acidosis, hypoxia and cell-to-cell uncoupling	***[23–30]***
ventricular ectopic beats	localization with 12-lead ECG	***[31–34]***
ventricular tachycardia	localization of exit points with 12-lead ECG	***[29,35]***
cardiomyopathy	modeling typical changes of QRS- and T-wave	***[36-53]***

The literature survey yielded several articles that do not focus on a specific disease butrather deal with the general concept of calculating the ECG from computer models of the heart. Lyon et al. gave an outline of a computational pipeline, listed examples of modeling diseases together with the ECG and showed up several applications of modeling in ECGinterpretation . Potse suggested a fast method for realistic ECG simulation without oversimplifying the torso model by using a lead-field approach . Building upon this approach, Pezzuto et al. found an even faster method that allows for implementation ona general-purpose graphic processing unit (GPGPU) . Keller et al. investigated the influence of tissue conductivities on the resulting ECG Schuler et al. found a way to down sample the fine grid necessary for calculating the spread of depolarization for theforward calculation of the ECG—further reducing calculation time. Neic et al. developed are action eikonal algorithm that simulates the spread of depolarization very fast and stilldelivers realistic ECGs .Calculation times for computing the spread of depolarization and repolarization,the lead field matrix and the body surface potentials including the ECG strongly depend onthe methods employed: highly detailed cell models versus simplified phenomenologicalmodels, high versus low spatial resolutions, etc. They can range from one day down to onesecond. As an example, the calculation times of the P-waves shown

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in Figure1 were 27 h for the full bidomain model and the Courte manche cell model, 1 h and 24 min for a pseudo bido main model and 40 min for a monodomain simulation (heart mesh with 4.7 million elements and 920 k nodes, desktop computer with 12 cores at 1.4 GHz). Fast calculation times are important for the researcher aiming at the identification of new features in the ECG, for creating a training dataset for machine learning and for personalization of a heart model. They are not relevant any more if, for example, a machine learning algorithm is finally used in clinics.

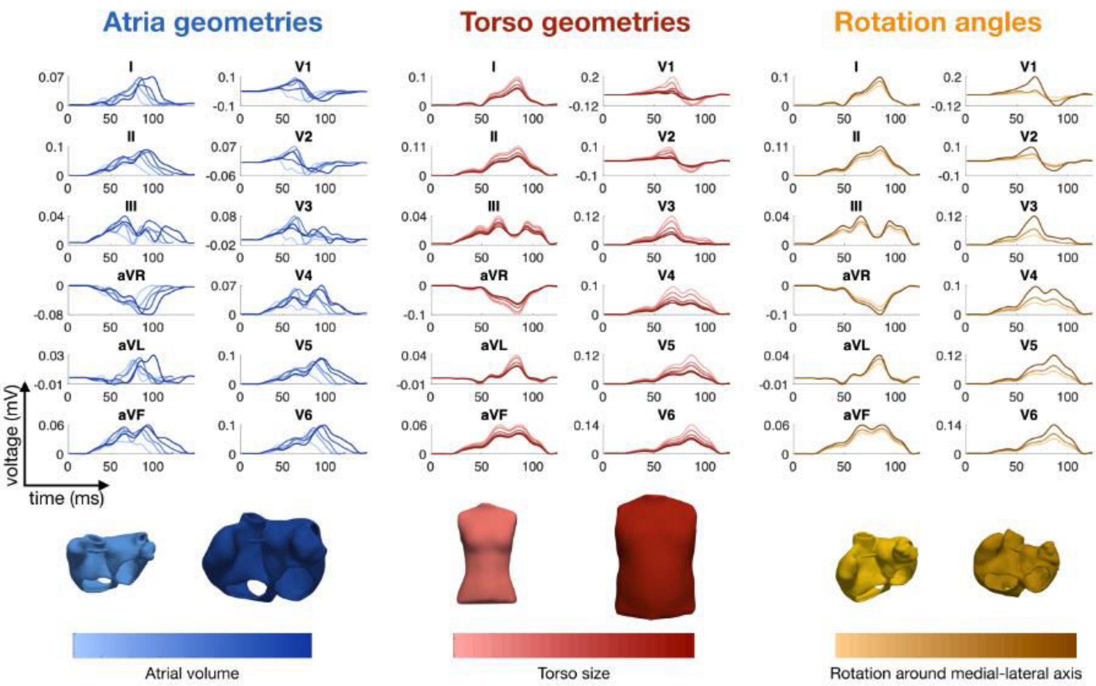

Figure 1. Simulated P-waves of the 12-lead ECG with various atrial shapes, several orientations of the atria inside the torso and a variety of body shapes. The colors represent the total atrial volume inblue, the torso size in red and the orientation angle around the medial-lateral axis in orange

Elimination of Noise from the ECG Signal

ECG noise is ubiquitous; it is present in operating rooms, in physiological laboratories, and in patient wards. Noise from power line interference (50 or 60 Hz), EMG from muscles, motion artifact from the electrode and skin contact interface, and multi-frequency noise due to electronic equipment in the surroundings of the patient are the various types of interference that contaminate an ECG signal. Elimination of this ECG noise is, therefore, the first step in ECG analysis and interpretation. However, removal of multiple frequencies is not a simple process. Suppression of noise usually causes ECG signal distortion leading to inaccurate interpretation. In spite of this stringent condition that imposes a trade-off between obtaining a noise free ECG, and accuracy of ECG analysis and classification, researchers have developed a number of techniques to extract useful diagnostic features from ECG signals contaminated by different types of interference. Some of these methods require pre-processing for noise elimination prior to feature extraction, while some detect the ECG characteristic in presence of noise.

In 1995, Ider et al. proposed a technique for removal of power line interference from signal averaged ECGs. The method was referred to as the Line Interference Subtraction filter (LIS) and was based on the subtraction of a scaled and shifted version of a common mode line interference signal, simultaneously recorded, from the ECG. To suppress the transient response of IIR notch filter, used for eliminating AC interference in ECG, Pei and Tseng, in 1995 , presented a technique based on the vector projection of the first few samples of the input signal (responsible for transient behavior). The method performed better than the conventional notch filter with arbitrary initial condition, by providing better initial values for the IIR notch filter output. Sahambi et al. , used wavelet transform to obtain multi-scale analysis for timing characterization of the ECG. The technique helped to detect the QRS-complex, P and T-waves with positive and negative polarity, PR, QT and ST-segments in the presence of noise, without preprocessing the signal. Baseline drift, power line interference, and a combination of both were the interference considered. The wavelet employed was the first derivative of a smoothing

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function (Gaussian function), that reduced errors, in ECG timing interval characterization, in the presence of noise. The technique was tested using records 106 and 202 of the MIT/BIH database. Ma et al., in 1999 , presented a fast recursive least squares (FRLS) adaptive notch filter (ANF) for removal of sinusoidal interference from recorded biomedical signals, including ECGs contaminated by 50/60 Hz power line interference. Rakotomamonjy et al. described a new wavelet-based filtering method to improve the signal-to-noise ratio of the signal averaged ECGs.

Removal of Baseline Wander from the ECG Signal

The iso-electrical period in electro-cardiology is the reference against which the instantaneous magnitudes of ECG signal components are determined. This period is not a clearly defined portion of the ECG, especially when the heart rate is high enough, making this period too short to be used or not present at all. Ideally, the reference level against which the magnitude of the recorded ECG is to be measured should represent zero activity of the signal source. Unfortunately, in most cases the zero level of ECG signal deviates from zero voltage, and it is generally difficult to determine its exact value [34]. However, the idea of the isoelectric period of the recorded ECG being taken as the reference level is not sufficient, and, that the isoelectrical period in the ECG denotes the true level of zero heart action does not produce desired results. Difficulty in determining the exact instant when ventricular activity ends, the end of the T-wave extending into the assumed isoelectrical period, high heart rate, distortion of the signal by EMG, respiratory activity creating baseline wander, render discrimination between the tail of the T-wave and the onset of isoelectrical period quite problematic and deformation of the ECG signal during the assumed isoelectrical period by ischemic currents flowing through the heart create numerous difficulties in determining the exact baseline in an ECG to accomplish feature extraction. As per CSE Working Party's updated AHA recommendations , the ST- segment, the T-wave and the P-wave, should all be measured with respect to the isoelectric part of the tracing before the P-wave. CSE Working Party recommended that a uniform horizontal baseline should be determined in an interval before QRS-onset for all QRS and ST-T measurements in such a way so that problems arising due to the earlier AHA recommendations, in which a discontinuity is implied in the baseline immediately after the J point, could be avoided.

Identification of QRS-Complexes

ECG is characterized by a recurrent wave sequence of P, QRS and T-wave associated with each beat. The QRS-complex is the most striking waveform, caused by ventricular depolarization of the human heart. Once the positions of the QRS-complexes are found, the locations of other components of ECG like P-wave, T-wave and ST-segment, etc. are found relative to the position of QRS, in order to analyze the complete cardiac period. In this sense, QRS-detection provides the fundamental basis for almost all automated ECG analysis algorithms. The QRS-wave is used as the basis for faithful heart disease diagnosis, for carrying out studies on HRV and for analysis of arrhythmia. The rapid development of powerful computers promoted the widespread application of software for QRS-detection in cardiological devices. The QRS-detection algorithms developed so far can be broadly classified into seven main categories.

Identification Based on Heuristic Approach

The heuristic methods are based on the temporal characteristics of the signal such as its amplitude, first and second derivative. These methods are noise sensitive but simple to implement. Pan and Tompkins have developed a real-time algorithm for the detection of QRS-complexes of the ECG signal. It reliably recognizes the QRS-complexes based upon digital analysis of amplitude, slope and width. Fraden and Neuman used amplitude and first derivative to detect QRS-complex, Fancott and Wong and Cox et al. used first derivative. When it exceeds threshold it detects QRS-complex. Murthy and Rangaraj used transformed first order derivative of amplitude for detection of QRS-complex. Ahlstrom and Tompkins used both first and second order derivative for detection of QRS-complex. Engelse and Zeelenberg used the sum of rectified smoothed first derivative and rectified second derivative to set primary and secondary thresholds. If the sum of first and second derivative exceeds secondary threshold, a QRS-complex is detected but this algorithm is noise sensitive. Ferdi et al. used fractional digital differentiation for the detection of R-wave in the ECG signal. Arzeno et al. made quantitative analysis of three QRS-detection algorithms by applying different transforms on the differentiated ECG signal (first derivative). The three transforms used are the Hilbert transform, the squaring function and a second discrete derivative stage. The Hilbert transform and the squaring function performs better as compare to the second derivative.

Identification Based on Mathematical Transformations

In this category, various mathematical transformations, namely Fourier transform, cosine transform, differentiator transform, Hilbert transform and wavelet transform are used for the QRS-detection. The use of these transforms on ECG signal helps to characterize the signal into energy, slope, or spike spectra and thereafter, the temporal locations are detected with the help of decision rules like thresholds of amplitude, slope, or duration. The non-linear transformation of the signal is done by Weinsner et al. , Fancott and Wong and Murthy and Rangaraj. The transformation results in a single positive peak with no ripples for each ECG cycle with maximum value occurring at

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the end of the QRS-complex. The maximum value is used for QRS-detection. Murthy and Prasad proposed a solution to the fundamental problem of ECG analysis, viz. delineation of the signal into its component waves. The discrete cosine transform of a bell shaped biphasic function is approximated mathematically by a system function with two poles and two zeros. A one-to-one relation between the pole pattern in the z-plane and the component wave pattern in the time signal is established. Ghaffari et al. proposed a mathematical based QRS-detector using continuous wavelet transform. Benitez et al. developed an algorithm for the detection of QRS-complexes using the first differential of the ECG signal and its Hilbert transformed data to locate the R-wave peaks in the ECG waveform. The differentiation of R-waves from large and peaky P and T-waves is achieved using this algorithm.

There are some algorithms, which work on the use of mathematical approaches like mixed mathematical basis function, mathematical models, mathematical morphology, spatial velocity function, entropy concept and averaging techniques. Mathematical models are developed by considering the QRS-segment as pulse shaped waveform and its variables as the number of peaks, arrival time, amplitude and width of various complexes . The mixed mathematical functions like Gaussian, exponential and straight line have been used to represent the composite ECG signal. Sornmo et al. have considered the mathematical model for the occurrence of pulse shaped waveforms corrupted with colored Gaussian noise. The number of waveforms, the arrival times, amplitudes and widths are regarded as unknown variables. Adaptivity of the detector is gained by utilizing past as well as future properties of signal in determining thresholds for QRS-acceptance. Naima have presented two approaches for feature extraction of the ECG signal for computer-aided analysis. The first approach is based on mixed mathematical functions and second one on spline functions. These methods also identify and separate P, Q, R, S and T-segments. These methods are suitable for memory based manipulations and mapping type microcomputer based biomedical instruments. Park et al presented an algorithm detecting the presence of a fetal QRS-complex. It computes the averaged magnitude of the difference between the fetal ECG signal and the reference signal to detect the fetal QRS-event. Trahanias suggested an approach based on mathematical morphology for QRS-detection.

Identification Based on Various Pattern Recognition Techniques

This category of algorithms includes pattern recognition techniques for the detection of QRS-complex. In syntactic approach of ECG pattern recognition, the ECG signal is first reduced into a set of elementary patterns like peaks, durations, slopes and inter-wave segments and thereafter rule based grammar is used. The signal is represented as a composite entity of peaks, durations, slopes and inter-wave segments. These patterns are then used to detect the QRS-complexes in the ECG signal. The methods of this category are time consuming and require inference grammar in each step of execution for QRS-detection. Even then the motivation for using syntactic approach resides in the fact that human inspection of ECG waveforms is firstly an extraction of structural and qualitative information. Once this information has been obtained and some typical forms (like a QRS-complex) have been recognized, the numerical values of the durations and amplitudes useful for diagnosis are measured.

Mehta et al. used pattern recognition technique for the detection of QRS-complexes in the ECG signal. Lin and Chang , Pietka , Udapa and Murthy used synaptic method for QRS-detection. In this, a set of priitive are decided which should provide adequate description of ECG. Then parameter such as slope and height are determined. This method is based on the assumption that the ECG is composed of peaks and segments, which are primitives that constitute the ECG. Peaks are combined to form complex. The complex and segments are combined to form cardiac cycles. Gustavo et al. used the syntactic method to extract the time evolution of the rhythm using the energy of ECG derivatives and their coding by a look up table method. Trahanias and Skordalakis have reported a bottom-up approach to the recognition of ECG waveforms. This approach is based on the assumption that ECG waveforms are composite entities that can be decomposed into other simpler entities, further into other simpler ones and so on, until peak patterns and segment patterns are obtained. After recognition of these primitive patterns, recognition of the ECG patterns using bottom-up procedure has been carried out. In their other paper, solutions to the sub-problems of primitive pattern selection, primitive pattern extraction, linguistic representation and pattern grammar formulation are reported. They observed that the primitive pattern extractor does not always accurately delineate the boundaries of the peak patterns. This type of error is propagated in the next stages and is responsible for many inaccurate results. Looking to the complex structure with infinite morphological variability, this approach faces difficulty in QRS-detection.

Identification Based on Artificial Neural Networks and Fuzzy Logic

An improvement over the methods discussed above, the concept of adaptiveness has been introduced in the techniques used for QRS-detection. Adaptive thresholds for signal amplitude, slope, entropy and durations, adaptive matched filtering, adaptive estimation of QRS-segment features by the Hermite model, neural network based adaptive matched filtering and adaptive template buildings are some of the techniques in this category. In these techniques, an algorithm configures itself to a unique QRS-segment of a patient during an initial stage of learning. Singhvi used adaptive threshold on the slope of the ECG signal for the detection of QRS-complexes. Paliwal applied adaptive threshold on the entropy of ECG signal for localization of QRS-complexes. Recently, Chouhan and Mehtaproposed a technique of adaptive quantized threshold for the detection of QRS-complexes in single-lead electrocardiogram. This adaptability approach enhances the QRS-detection rate by a considerable extent and reduces the percentage of false detections, but at the same time, increases the computations as it involves learning phase (determination of adaptive model parameters) and repetitive calculations to optimize the threshold limits for amplitude, slope and durations.

Identification of P and T-waves in ECG Signal

The detection of P and T-wave is more difficult than QRS-complex detection for several reasons including low amplitudes, low signal-to-noise ratio, amplitude and morphological variability and possible overlapping of the P-wave with T-wave or the QRS-complex in case of high heart beat rate. The P-wave may be even absent from some ECG recordings. Over the last few years, the P and T-wave detection and delineation problem has been addressed using different approaches.

Rey et al. developed an algorithm for the detection of P-waves and tested on seven patients with various arrhythmias. Hengeveld and Bemmel have presented two algorithms for the detection of P-waves in ECG's. The first algorithm makes use of the stability of PR-intervals for the detection of the coupled P-waves and the second one, for the detection of non-coupled P-waves computes the cross-correlation between a ternary detection signal, derived form the original ECG and a template, obtained from a reference population of P-waves. The methods have been tested on two sets of recordings, one with complicated rhythms and wave shapes and the other with material of average clinical patients. Brodda et al. proposed a procedure for searching a P-wave in the corrected orthogonal electrocardiogram (VCG) on the basis of VCG representation in spherical coordinates. Reddy et al. done a preliminary study for the detection of P-waves in resting ECG in which median QRS-ST-segments were subtracted form the rhythm data and residual in the QRS-regions was zeroed. Resulting signals were low passed filtered, first and second differenced and combined into a detection function, which was used to detect and delineate P-waves. Fokapu and Girard proposed an algorithm for P-wave detection which uses the instantaneous frequency of ECG analytic signal. Zhu proposed an algorithm for the detection of P-waves based on an adaptive QRS-T-cancellation technique. Sabry-Rizk et al.reported a strategy for P-wave detection utilizing non-linearly synthesized ECG components and their enhanced pseudo-spectral resonances. Sovilj et al. developed a real time P-wave detector based on wavelet analysis. Senhadji et al. proposed a method for the detection of P-waves after beat-to-beat QRS-T cancellation based on wavelet transform.

Vila et al. have presented a T-wave detection and shape classification algorithm using a mathematical signal modeling stage prior to the detection and characterization of the T-wave by standard geometric technique. Mehta et al. developed fuzzy theory based pattern recognition technique for correct identification of P and T-waves. Freeman and Singh developed an algorithm for the detection of P-waves in ambulatory ECG. Sivannarayana and Reddy used bio-orthogonal wavelet transform for ECG parameters estimation. Stamkopoulos et al. developed wave segmentation technique using non-stationary properties of ECG. Clavier et al. have performed automatic P-wave analysis of patients prone to atrial fibrillation. Vasquez et al. applied Wiener filtering using an artificial neural network for the enhancement of atrial activity. Domider et al. developed an approach to the P-wave detection and classification based upon application of wavelet neural network Le et al. used spatial velocity to detect P and T-waves. Murthy and Niranjan used discrete Fourier transform where as Murthy and Prasad used discrete cosine transform. Thakor and Zhu developed adaptive filters for delineation of P-waves. Trahanias and Skordalaki used attributed grammar for the detection of P-waves and T-waves. Mehta and Lingayat applied Support Vector Machine as a classifier for the detection and delineation of P and T-waves in simultaneously recorded 12-lead ECG.

Modeling Diseases and the Corresponding ECG

Loewe at al. gave an outline of how computer modelling can support comprehension of cardiac ischemia and discussed the link to the corresponding ECG . Figure2 shows several examples of ischemic regions together with the corresponding ECG. The parameters of the ten Tusscher–Panfilov cell model which reflect the degree and temporal stage ofthe occlusion were summarized by Wilhelms et al. . They considered the cellular effects due to hyperkalemia, acidosis and hypoxia as well as due to cellular uncoupling.After clarifying the origin of ST-segment elevation (and depression), they also demonstrated how several ischemic scenarios will not show any ST-segment change . Thus, they were able to explain the large group of non-ST-segment elevation myocardial infarctions(NSTEMI). Potyagaylo et al. showed that these scenarios are not only electrically but also magnetically “silent” . Loewe at alusing computer modelling investigated whether additional

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electrodes, optimized electrode placement or improved analysis of theST segment could lead to better diagnosis of patients with acute ischemia. They suggestthe deviation from baseline at the K-point as being superior to J-point analysis

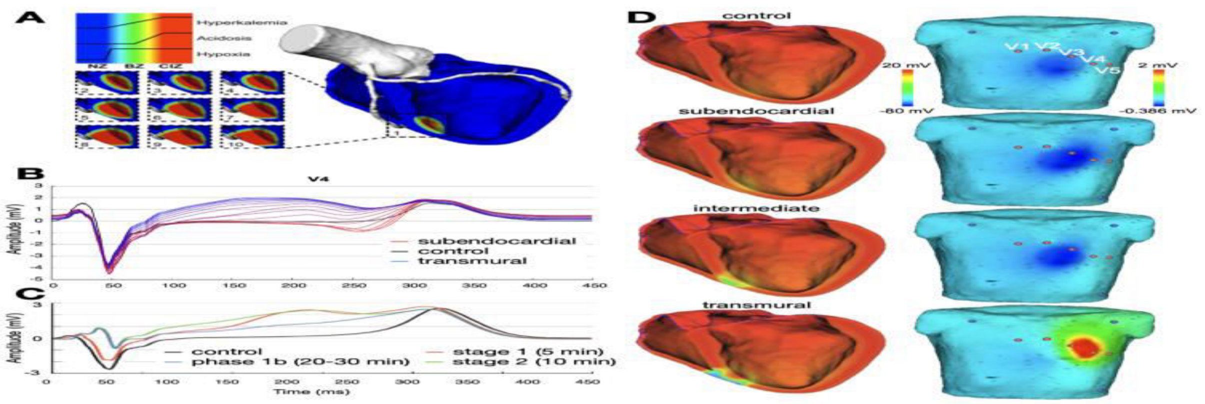

Figure 2. Examples of ischemic regions with varying transmural extent due to occlusion of the leftanterior descending coronary artery and the related levels of hyperkalemia, acidosis, and hypoxia (A).ECG lead V4 for ischemia of varying transmural extent in temporal stage 2 (B) and varying duration ofa transmural ischemia (C). Ventricular transmembrane voltage and body surface potential distribution during the action potential plateau (t = 200 ms) for ischemia of varying transmural extent in stage 2 (D).

Computerized ECG interpretation to detect arrhythmias (off-line or on-line) is a process of ECG data acquisition, waveform recognition, measurement of wave parameters and rhythm classification. Substantial progress has been made over the years in improvising techniques for signal conditioning, extraction of relevant wave parameters and rhythm classification. However, many problems and issues, especially those related to detection of long P and T peaks and reliable analysis of multiple arrhythmic events etc., still need to be addressed in a more comprehensive manner to brighten the prospect of commercial automated arrhythmia analysis in mass health care centers.

From the literature survey it is observed that besides conventional computing techniques such as FFT, DFT and wavelet transforms etc., frequent usage of sophisticated artificial intelligent tools such as expert systems has also been reported. Knowledge-based expert systems that are IF-THEN rule based systems form a major part of clinical decision support systems in practice, since the decision-making process in such systems is easily followed by a cardiologist. Non-knowledge-based expert systems that are not rule based employ hybrid AI techniques such as fuzzy-neural networks are fast and efficient, further research is needed to make them more reliable in clinical diagnostics. Also, these systems provide little insight into how decisions are made or what is the declarative knowledge structure, thereby creating difficulties for cardiologists to understand such 'black-box' systems, and hence eliciting their disapproval for implementation of such systems in clinical situations

3 Conclusion

This research article demonstrates an application of Genetic Algorithm (GA) for the effective automatic identification and delineation of ECG wave components such as P-wave, QRS-complexes, and T-waves in multi-channel ECG recordings. The basic theory of GA is given in order to give some basis for its application for the component wave detection.Establishing a stronger link between computer modelling of the heart and the ECG holds great potential. To consequently add at least the calculation of endocardial electrograms and compare with clinical data from the electrophysiology lab would add more evidence to computerized modelling of the heart. Moreover, the forward calculation of the ECG on the body surface is possible and allows for a comparison with the clinical ECG that is most often available. It is a valuable test of the consistency of the modelling approach and can lead to new insights about the relation between electrophysiological phenomena in the heart and the corresponding ECG . Likewise, if new (and most often computerized) methods of ECG analysis are proposed, it would be important to make the results explainable by mechanistically underpinning the results, e.g., by backing up the hypotheses with state-of-the-art computer simulations. In many cases, a "rule of thumb" using the classical heart vector for an explanationcan be misleading. If a feature in the ECG can be clearly linked to a source pattern on the heart, the diagnostic value of ECG can be increased.It might be possible to construct personalized models of the heart from the 12–lead ECG . However, often there will be ambiguities and spatially higher resolved BSPMs orintracardiac electrograms will be needed. There are also other options for

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personalization., measuring the ECG of a patient for one or two electrolytes or drug concentrations and using computer modelling to predict (interpolate) intermediate values can enable a quantitative interpretation of the ECG.For making general conclusions about features in the ECG that point to specific diseases, the analysis of computer simulations with just one geometry of heart and torsowill not be sufficient in the long run. In summary, bridging the gap between computerized modeling of the heart and ECG analysis (as well as intracardiac electrograms) holds great potential to lead to better comprehension of cardiac diseases, better diagnosis and optimized therapy planning.

REFERENCES

[1] Afonso V.X., Tompkins W.J., Nguyen T.Q. and Luo S., "ECG beat detection using filter banks," IEEE Transactions on Biomedical Engineering, vol. 46, no. 2, pp. 192-201, 1999.

[2] Ahlstrom M.L. and Tompkins W.J., "Automated high-speed analysis of Holter tapes with microcomputer," IEEE Transactions on Biomedical Engineering, vol. 30, no. 10, pp. 651-657, 1983.

[3] Alste Van J.A. and Schilder T.S., "Removal of baseline wander and power line interference from the ECG by an efficient FIR filter with a reduced number of taps," IEEE Transactions on Biomedical Engineering, vol. 32, no. 12, pp.1052-1059, 1985.

[4] Amazeem P.G., Moruzzi R.L. and Fieldman C.L., "Phase detection of R-wave in noisy ECGs," IEEE Transactions on Biomedical Engineering, vol. 19, no. 1, pp. 63-66, 1972.

[5] Arafat A. and Hasan K., "Automatic detection of ECG wave boundaries using Empirical Mode Decomposition," IEEE International Conference ICASSP 2009, pp. 464-464.

[6] Arnaud P., Rubel P., Morlet D., Fayn J. and Forlini M.C., "Methodology of ECG interpretation in the Lyon program," Methods of Information in Medicine, vol. 29, no. 4, pp. 393-402, 1990.

[7] Arzeno N.M., Poon C.S. and Deng Z.D., "Quantitative analysis of QRS-detection algorithms based on first derivative of the ECG," Proceedings of the 28th IEEE EMBS Annual International Conference, New York, USA, pp. 1788-1791, 2006.

[8] Bansal S.K., "An entropy based method for detection of QRS-complex using genetic algorithms," M.E. Thesis, Department of Electrical Engineering, J.N.V. University, Jodhpur, 2007.

[9] Barker J., "The unipolar Electrocardiogram: A Clinical Interpretation," Year Book Medical Publishers, Chicago, 1952.

[10] Bartoli F., Cerutti S. and Gatti E., "Digital filtering and regression algorithms for an accurate detection of the baseline in ECG signals," Med. Informatics, vol. 8, no. 2, pp. 71-82, April 1983.

[11] Bemmel Van J.H., Kors J.A. and Herpen Van G., "Methodology of the Modular ECG Analysis System MEANS," Methods of Information in Medicine, vol. 29, no. 4, pp. 346-353, 1990.

[12] Ben M., "On the algorithm for QRS-complexes localization in ECG," International Journal of Computer Science and Network Security, vol. 7, no. 5, pp. 28-33, 2007.

[13] Benitez D., Gaydecki, P.A., Zaidi, A. and Fitzpatrick A.P., "The use of Hilbert transform in ECG signal analysis," Computers in Biology and Medicine, vol. 31, no. 5, pp. 399-406, 2001.

[14] Bezdek J. C., "Pattern Recognition with fuzzy objective function algorithms," Plenum Press, New York, 1981.

[15] Bland J. M. and Altman D. G., "Measuring agreement in method comparison studies," Statistical Methods in Medical Research, vol. 8, pp. 135–160, 1999.

[16] Brailer D.J., Kroch E. and Pauly M.V., "The impact of computer assisted test interpretation on physician decision making," Medical Decision Making, vol. 17, no. 1, pp. 80-86, 1997.

[17] Brodda K., Wellner U. and Mutschler W., "A new method for detection of P-waves in Electrocardiograms," Signal Processing, vol. 1, no. 1, pp. 15-25, 1979.

[18] Brohet C.R., Derwael C., Robert A. and Fesler R., "Methodology of ECG interpretation in the Louvain program," Methods of Information in Medicine, vol. 29, no. 4, pp. 403-409, 1990.

[19] Caroubalos C., Perche C., Metaxaki-Kossionides C., Sangriotis E. and Maroulis D., "Method for automatic analysis of the ECG," Journal of Biomedical Engineering, vol. 10, no. 4, pp. 343-347, 1988.

[20] Chavan M.S., Agarwala R.A. and Uplane M.D., Design and implementation of digital FIR equiripple notch filter on ECG Signal for removal of power line interference, WSEAS Trans. Signal Processing, vol. 4, no. 4, pp. 221-230, 2008.

[21] Chawla M.P.S., Verma H.K. and Kumar V., "Artifacts and noise removal in electrocardiograms

using independent component analysis," International Journal of Cardiology vol. 129, no: 2, pp. 278-281, 2008.

[22] Chawla M.P.S., Verma H.K. and Kumar V., "Detection of R-peaks in electrocardiograms using independent component analysis," International Journal of Cardiology, vol. 129, no: 1, pp. 146-148, 2008.

[23] Chen, S.W., Chen H.C. and Chan, H.L., "A real time QRS-detection method based on moving-averaging incorporating with wavelet denoising," Computer Methods and Programs in Biomedicine, vol. 82, no. 3, pp. 187-195, 2006.

[24] Chouakri, S.A., Bereksi-Reguig A, Taleb-Ahmed A, "QRS complex detection based on multi wavelet packet decomposition," Applied Mathematics and Computation, vol. 217, no. 23, pp. 9508-9525, 2011..

[25] Chouhan V. S. and Mehta S. S., "Total removal of baseline drift from ECG signal," International Conference on Computing Theory and Applications, pp. 512-515, 2007.

[26] Chouhan V.S. and Mehta S.S., "Detection of QRS-complexes in 12-lead ECG using adaptive quantized threshold," International Journal of Computer Science and Network Security, vol. 8, no.1, pp. 155-163, 2008.

[27] Chouhan V.S. and Mehta S.S., "Threshold-based detection of P and T-wave in ECG using new feature signal," International Journal of Computer Science and Network Security, vol. 8, no. 2, pp. 144-153, 2008.

[28] Christov I., Herrero G.G., Krasteva V., Jekova I., Gotchev A. and Egiazarian K., "Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification," Medical Engineering and Physics, vol. 28, no. 9, pp. 876-887, 2006.

[29] Clark W.A. and Molnar, C.E., A description of the LINC, Computers in Biomedical Research, R.W. Stacy and B.D. Waxman, Eds., New York: Academic Press, vol. 2, pp. 45-66, 1965.

[30] Clavier L., Boucher J.M., Lepage R., Blanc J.J. and Cornily J.C., "Automatic P-wave analysis of patients prone to atrial fibrillation," Medical and Biological Engineering and Computing, vol. 40, no. 1, pp. 63-71, 2002.

[31] Clifford G. D., Azuaje F., McSharry P. E., "Advanced methods and tools for ECG data analysis," Artech House, 2006.

[32] Cohen D. and Kaufman, L.A., "Magnetic determination of the relationship between the S-T segment shift and the injury current produced by coronary artery occlusion," Circ. Res., vol. 36, pp. 414-424, 1975.

[33] Cox J.R., Nolle F.M, Fozzard H.A. and Oliver G.C., "AZTEC, a preprocessing program for real time ECG rhythm analysis," IEEE Transactions on Biomedical Engineering, vol. 15, no. 1, pp. 128-129, 1968.

[34] Cox J.R., Jr. and Logue R.D., "Some observations on the economics of computer systems for monitoring electrocardiographic rhythms," Comput. Biomed. Res., vol. 4, pp. 447-459, 1971.

[35] Cox J.R., Jr., Nolle F.M. and Arthur R.M., Digital analysis of the electroencephalogram, the blood pressure wave, and the electrocardiogram, Proc. IEEE, vol. 60, pp. 1137-1164, 1972.

[36] Dandapat S. and Ray G.C., "Spike detection in biomedical signals using midprediction filter," Medical and Biological Engineering and Computing, vol. 35, no. 4, pp. 354-360, 1997.

[37] Dave V., "Detection of QRS-complexes in 12-lead ECG using error back propagation artificial neural network," M.E. Thesis, Department of Electrical Engineering, J.N.V. University, Jodhpur, 2004.

[38] Degani R. and Bortolan G., "Methodology of ECG interpretation in the Padova program," Methods of Information in Medicine, vol. 29, no. 4, pp. 386-392, 1990.

[39] Domider T., Tkacz E.J., Kostka P., Wrzesniowski A., "A new approach to the P-wave detection and classification based upon application of wavelet neural network," Proceedings of the 23rd IEEE EMBS Annual International Conference, Istanbul, Turkey, pp. 1758-1760, 2001.

[40] Dunn J. C., "A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters," J. Cybernet., vol. 3, pp. 32-57, 1974.

[41] Einthoven W., The telecardiogram, Arch. Int. Physiol., 1906, vol. 4, pp. 132-161 (Transl.: F.A.L. Mathewson and H. Jackh, Amer. Heart J., 1955, vol. 49, pp. 77-82, and H.W. Blackburn, Jr., Amer. Heart J., 1957, vol. 53, pp. 602-615).

[42] Engelse W.A.H. and Zeelenberg C., "A single scan algorithm for QRS-detection and feature extraction," Proceedings of Computers in Cardiology, vol. 6, pp. 37-42, 1979.

[43] Escalona O.J., Mitchell R.H., Balderson P.E. and Harron D.W.G., “Fast and reliable QRS-alignment technique for high-frequency analysis of signal-averaged ECG,” Medical and Biological Engineering and Computing, vol. 31, no. 1, pp. 137-146, 1993.

[44] Fancott T. and Wong D.H., “A mini computer system for direct high speed analysis of cardiac arrhythmia in 24 hrs ambulatory ECG tape recording,” IEEE Transactions on Biomedical Engineering, vol. 27, no. 12, pp. 685-693, 1980.

[45] Fard J. M., Moradi M. H., and Tajvidi M. R., “A novel approach in R peak detection using Hybrid Complex Wavelet,” Int. J. Card., 2007, doi:10.1016/j.ijcard.2006. 11.136.

[46] Ferdi Y., Herbeuval J.P., Charef A. and Boucheham B., “R-wave detection using fractional digital differentiation,” ITBM-RBM, vol. 24, no. 5-6, pp. 273-280, 2003.

[47] Fokapu O.and Girard J.P., “A new approach for P-wave detection using analytic signal,” Proceedings of the 15th IEEE EMBS Annual International Conference, pp. 400-401, 1993.

[48] Fraden J. and Neuman M.R., “QRS-wave detection,” Medical and Biological Engineering and Computing, vol. 18, no. 2, pp. 125-132, 1980.

[49] Franz Rothlauf, “Representation for Genetic and Evolutionary Algorithms”, Springer, Heideiberg New York, 2006.

[50] Freeman K. and Singh A., “P-wave detection of ambulatory ECG,” Proceedings of the 13th IEEE EMBS Annual International Conference, vol. 13, no. 2, pp. 647-648, 1991.

[51] Froelicher V.F.J., Wolthius R., Keiser N., Stewart A., Fischer J., Longo M.R.J., Triebwasser J. H. and Lancaster M. C., “A comparison of two bipolar exercise electrocardiographic leads to lead V5,” Chest, vol. 70, no. 5, pp. 611–616, 1976.

[52] Furno G.S. and Tompkins W.J., “A learning filter for removing noise interference,” IEEE Transactions on Biomedical Engineering, vol. 30, no. 4, pp. 234-235, 1983.

[53] Garg A.R., “Detection of QRS-complex in Electrocardiograms using artificial neural networks,” M.E. Thesis, Department of Electrical Engineering, J.N.V. University, Jodhpur, 2002.