A Unified Approach of ECG Signal Analysis

Rajiv Ranjan, V. K. Giri

Abstract: ***The bio-potentials generated by the muscles of the heart result in an electrical signal called electrocardiogram (ECG). It is one of the most important physiological parameter, which is being extensively used for knowing the state of the cardiac patients. Feature extraction of ECG is most essential task in the manual and automated ECG analysis for use in instruments like ECG monitors, Holter tape recorders and scanners, ambulatory ECG recorders and analysers. Recently, artificial intelligent tools such as neural networks, genetic algorithms, fuzzy systems, and expert systems have frequently been reported for detection and diagnostic tasks. This paper, therefore, is an attempt to review the work done by the different researchers in the area of ECG signal processing, analysis and interpretation during last five decades.***

Keywords: ***Arrhythmia, ECG analysis, ECG interpretation, Noise removal, Expert system, Artificial intelligence, Feature extraction.***

I. INTRODUCTION

Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mV. The ECG signal is characterized by five peaks and valleys labelled by the letters P, Q, R, S, T as shown in fig1. In some cases (especially in infants) we may also find another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T and P waves. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment *etc.* can be performed. In the normal sinus rhythm (normal state of the heart) the P-Rinterval is in the range of 0.12 to 0.2 seconds as shown in fig 1. The QRS interval is from 0.04 to 0.12 seconds.

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Rajiv Ranjan, Associate Professor, Department of Electrical & Electronics Engineering, Dronacharya Group of Institutions, Gr. Noida U.P. India .

Dr. V.K. Giri, Professor, Electrical Engineering Department, MMM Engineering College, Gorakhpur, U.P. India.

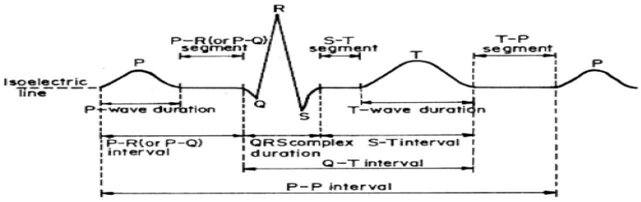

Figure 1.The normal ECG signal.

The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal. The electrocardiogram is a graphic recording or display of the time variant voltages produced by the myocardium during the cardiac cycle. The P-, QRS- and T-waves reflect the rhythmic electrical depolarization and repolarization of the myocardium associated with the contractions of the atria and ventricles. This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart. The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (slow heart rate) and a higher rate is called tachycardia (fast heart rate). If the cycles are not evenly spaced, an arrhythmia may be indicated. If the P-R interval is greater than 0.2 seconds, it may suggest blockage of the AV node. The horizontal segment of this waveform preceding the P-wave is designated as the baseline or the isopotential line. The P-wave represents depolarization of the atrial musculature. The QRS complex is the combined result of the repolarization of the atria and depolarization of the ventricles, which occur almost simultaneously. The T-wave is the wave of ventricular repolarization, where as the U-wave, if present is generally believed to be the result of after potentials in the ventricular muscle. So, the duration amplitude and morphology of the QRS complex is useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial infection and other disease states**.** Various abnormalities and their characteristic features are listed in table 1.

II. RESEARCH WORK & LITERATURE REVIEW AT A GLANCE

Although the first attempt to automate ECG analysis by digital computer was made as early as in 1956 by Pipberger and his group, but the first industrial ECG processing system came in the market during seventies. Since then many investigative and commercial minicomputer-based and microcomputer based system have become common in use. It took considerable time to develop operational computer programs than originally anticipated. However, over last 15 years, research groups have mainly developed the computer programs but in last decade, the development has shifted to industry. Computers can assist a cardiologist in the task of ECG monitoring and interpretation. For example, in a cardiac intensive care unit (CICU), ECGs of several patients must be monitored

Table 1: Various abnormalities and their characteristic feature

Sr. No	Name of abnormality	Characteristic features
1.	Dextrocardia	Inverted P-wave
2.	Tachycardia	R-R interval < 0.6 s
3.	Bradycardia	R-R interval > 1 s
4.	Hyperkalemia	Tall T-wave and absence of P-wave
5.	Myocardial	Ischaemia Inverted T-wave
6.	Hypercalcaemia	QRS interval < 0.1 s
7.	Sinoatrial block	Complete drop out of a cardiac cycle
8.	Sudden cardiac death	Irregular ECG.

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 during all 24 hours in a day, automated monitors programmed to detect abnormal heart rhythms are needed. Over the past several years, the computerised 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 bed side 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's records and database.In the past five 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 scarce. Each ECG programs has different principle with respect to analysis, for example, some measure single bits, whereas others analyse average bits. Until recent past, 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 difference result in measurements by different computer programs and hampers the exchange of diagnostic criteria and interpretation results [1]. In order to overcome some of these problems, a concept action was started by European Community (EC) in June 1980, striving towards 'Common Standards for quantitative Electrocardiography' (CSE) [2]. Pipberger *et al* [3] developed an automatic vectorcardiographic analysis (AVA) program during 1956. Signal recognition in this software is based on the spatial velocity function. Multivariate statistical analysis on orthogonal ECG leads assesses probabilities of nine alternative disease categories, base on QRS-T parameters. Okajima *et al* developed an ECG analysis and interpretation program during 1960, named as Nagoya program. In Japan, it is being utilized, with some modifications, for interpreting or monitoring the VCG, exercise ECGs, arrhythmia detection in the CCU, ambulatory ECGs, and body-surface mapping of the ECG. Disease diagnosis is based on the use of scoring schemes. Bemmel *et al* had introduced their MEANS (modular ECG analysis system) in 1972 and first published in 1974. This system was intended to be applied both for the clinical use and population screening and the MEANS was able to classify according to conventional clinical criteria as well as the Minnesota code. They have used the technique of cross correlation with the template and a matched filter for detection of ECG waves and decision tree classifiers for disease diagnosis [4].

Macfarlane *et al* [5] reported current Glasgow 12-lead ECG program. Its origin goes back to year 1977. It is designed to analyse from 3 to 15 simultaneously recorded leads with facilities for analysis of rhythm. Spatial velocity function is used for QRS detection and the wave typing is carried out using an iterative process and a set of rule- based criteria is used for interpretation of the P, QRS and T morphology. The Dalhousie ECG analysis program (DALECG) is a collection of relatively loosely coupled program modules that can be combined in various ways for processing the rest and exercise the ECG. The program was designed particularly for research application. Family of templates has been used for ECG analysis and the Minnesota code supplemented by several newer ECG classification schemes suitable for computer coding have been used by Rautaharju *et al* [6]. For diagnostic classification, a hybrid model with decision trees and scoring algorithms has been used by the Zywietz *et al* [7]. Methodology of ECG interpretation in the Padova program developed by Degani and Bortolan [8] is based on the use of spatial velocity functions for signal analysis and of fuzzy classifiers for disease interpretation.

Arnaud *et al* [9] developed the Lyon program to interpret VCGs using heuristic procedures to extract not a simple and unique interpretation, but several diagnostic hypotheses in accordance with the spatiotemporal structure of the QRS-T electrical field. The Louvain program performs the analysis and interpretation of the VCG to increase the clinical utility of ECG analysis. Wave recognition techniques in which a mixture of threshold-crossing and template- matching methods are applied to filter spatial velocity curves. A deterministic method is one in which the cardiologist's expertise is applied through Boolean algebra and decision tree logic in order to reach a diagnostic decision. A computer program for ECG analysis and interpretation developed at the University of Porto in Portugal is reported by Abreu-Lima and Marques [10]. The program employs the three-lead Frank VCG and detection of QRS complexes is based on the double threshold method for the spatial velocity amplitude and its time derivative. The fiducial points of all the ECG wave components are then detected using an exhaustive sequential search algorithm. The decision tree logic is being used for diagnosis.

Some of the internationally available ECG analysis and interpretation programs have been discussed above. Programs reported above use ECG and VCG and carry out interpretation based on decision logic or statistical analysis. Pipberger *et al* reported that the automated ECG diagnosis could be no better than the accuracy of the waveform detection that provides its measurement values. Similarly, Okajima *et al* reported that there are still many occasions of mistakes in fiducial point recognition or contour classification agreed upon unanimously. The revisions and modifications of the program are continuously in progress. The modular ECG analysis system (MEANS) consists of modules for signal analysis and diagnostic classification. All modules underwent many changes as a function of experience, insight and continuously changing information technology. Macfarlane has also reported that there will be continuous enhancement in the system if the more widely ECGs are interpreted on a particular system. The success of the reported techniques for processing ECG signal were demonstrated mostly through their processing on single lead or using the ECGs which do not belong to a standard database. 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 use of new techniques.

III. FEATURE EXTRACTION OF ECG SIGNAL

It has now gone beyond the capacity of the expert cardiologist to take care of large numbers of cardiac patients efficiently & effectively. Therefore, computer- aided feature extraction and analysis of ECG signal for disease diagnosis has become the necessity. The first step in computer aided diagnosis is the identification & extraction of the features of the ECG signal. The QRS complex is the most prominent feature and its accurate detection forms the basis of extraction of other features and parameters from the ECG signal. There are a number of methods, some of which deal with detection of ECG wave segments, namely P, QRS and T, while others deals with detection of QRS complexes. A good amount of research work has been carried out during the last five decades for the accurate and reliable detection of QRS segment in the ECG signal. The QRS detection algorithms developed so far can be broadly placed into four categories: (i) syntactic approach (ii) non-syntactic approach (iii) hybrid approach and (iv) transformative approach.

A. Syntactic Approach

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

B. Non-syntactic Approach

Non-syntactic type is the most widely used class of ECG feature extraction techniques. In this class, we find the use of amplitude, slope and threshold limit as well as the use of different filters, mathematical functions and models. Okada reported a five step digital filter, which removes components other than those of QRS complex from the recorded ECG [11]. The final step of the filter produces a square wave and its on-intervals correspond to the segments with QRS complexes in the original signal. Thakor *et al* carried out power spectral analysis of ECG waveform, as well as of isolated QRS complexes and episodes of noise and artifacts [12]. A band pass filter was used to maximize the signal (QRS complex) to noise (T-waves, 60 Hz, EMG etc.) ratio to detect the QRS complex. Due to the inherent variability of ECG from different persons, as well as variability due to noise and artifacts, the filter design was suboptimal in specific situations. Pan and Tompkins developed a real-time algorithm for detection of the QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analysis of slope, amplitude and width [13]. Hamilton and Tompkins have investigated the quantitative effects of number of common elements of QRS detection rules using the MIT/BIH arrhythmia database [14]. Then a progressively more complex decision process for QRS detection by adding new detection rules and optimized decision rule process were developed. Laguna *et al* developed a method to automatically determine the characteristic points (onsets and offsets) of P, QRS and T waves in the multilead ECG signals from the CSE, DS-3 database [15]. The method makes use of a differentiated and low pass filtered ECG signal. Escalona *et al* developed a QRS alignment technique which is based on the accurate detection of a single fiducial point in the band pass filtered (3-30 Hz) QRS segment [16].

The mixed mathematical functions like Gaussian, exponential and straight line were used to represent the composite ECG signal. The number of waveforms, the arrival times, amplitude and widths are regarded as unknown variables. Adaptivity of the detector was gained by utilizing past as well as future properties of signal in determining thresholds for QRS acceptance. Naima and Saxena have presented two approaches for feature extraction of the ECG signal for computer aided analysis. The first method is based on mixed mathematical functions and the second one on spline functions. The methods also identify and separate P, Q, R, S and T segments. These methods are good for memory- based manipulations and mapping type microcomputer based biomedical instruments [17, 18]. Trahanias suggested an approach based on mathematical morphology for QRS detection. This morphological operator works as a peak-valley extractor [19].

Recently, some new techniques have also been developed base on artificial neural network, fuzzy logic and genetic algorithms for accurate QRS detection .In these approaches, the basic methodology is to learn and later on to generalize the knowledge gained through the learning process to identify the known QRS complexes out of an exhaustic set of the ECG segments.

The accuracy and reliability of QRS detection by these methods is dependent on the type of used training set. As an improvement over the methods discussed above, the concept of adaptiveness has been introduced in the techniques used for QRS detection [15]. Adaptive thresholds for signal amplitude, slope 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.

An adaptive filtering algorithm based upon an ANN for QRS detection has also been developed. The residual signal which contains mostly higher frequency QRS complex energy is then passed through a linear matched filter to detect the location of the QRS complex. This technique suffers from two problems: (i) The pass band of the QRS complex is different for different subjects and even for different beats of the same subjects and (ii) the noise and QRS complex pass-bands overlap. Adaptive Hermite Model Estimation System (AHMES) is presented by Laguna *et al* [20] for on-line beat-to-beat estimation of the features of the ECG signal. The AHMES is based on the multiple-input adaptive linear combiner, using succession of the QRS complexes and the Hermite functions as inputs. The procedure has been incorporated to adaptively estimate a width-related parameter. The system allows an efficient real-time parameter extraction for classification and data compression. The concept of alignment method based on the multiscale cross-correlation between the template and each detected beat are used in High-resolution electrocardiogram (HRECG) records with high noise levels [25].

C. Hybrid Approach

In hybrid approach, the syntactic and non-syntactic approaches are combined to detect the QRS complex. These are not in common use, as in syntactic approach, the trace is being made on actual morphology of the ECG signal and in non-syntactic approach; there is no consideration to maintain the morphology of the ECG signal.

D. Transformative Approach

Transformative Techniques, namely Fourier Transform, Cosine Transform, Pole –zero Transform, Differentiator Transform, Hilbert Transform and Wavelet Transform are being 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. Murthy and Prasad proposed a solution to the fundamental problem of ECG analysis, viz., delineation of the signal into its component waves [21]. In recent times, the use of Wavelet Transform (WT) in QRS detection has shown upper edge in terms of accuracy of detection, simplicity in calculations and no need of pre-processing.

Saxena *et al* developed a combined wavelet transform technique to analyze multilead ECG signals for cardiac disease diagnostics. Two wavelets have been used i.e. a quadratic spline wavelet (QSWT) for QRS detection and Daubechies six coefficient (Db-6) wavelet for P and T detection. Extensive testing using the fundamental ECGs has validated the software and the desired ECG parameters for disease diagnostics are extracted. The software has been validated by extensive testing using CSE DS-3 database and MIT/BIH database. A procedure has been evoked using ECG parameters with a point scoring system for diagnosis of cardiac diseases, namely tachycardia, bradycardia, left ventricular hypertrophy and right ventricular hypertrophy [22]. Saxena *et al* developed new wavelet (WT 6 and WT 7) and used for the detection of QRS segments from the ECG signal [23]. Paul et al have shown that the wavelet transform allows finding of coordinated atrial activity during ventricular fibrillation [24]. The performance of temporal and multiscale methods to align the QRS complexes in a single recording channel of different simulated high resolution ECG and Holter records have been analysed[25].ECG are being analysed and processed for so many applications like detection of obstructive sleep apnoea apart from cardiac surveillance. Martinez et al have presented and validated a wavelet-based ECG delineation system which performs QRS detection and provides the locations of the peak(s) of P,Q,R,S and T waves, and the P, QRS, and T wave boundaries using a single analysis stage: the dyadic wavelet transform of the ECG signal [26]. A new ECG signal simulation technique has been developed for the enhancement of the ECG identification algorithm design and testing [27]. Po-Ching Chen *et al* presented a new algorithm which automatically categorized T-wave morphologies and improved the precision of T -wave delineation by WT using multiscale differential operator [28].Automatic beat-segmentation and classification system based on a Markovian approach is proposed where ECG signal is analysed in two layers. At layer 0, the ECG signal is segmented in terms of the beat waveforms and at layer 1; the system identifies premature ventricular contraction beats [29]. Phillippe Ravier *et al* have redefined classical performance evaluation tools in entire QRS complex classification systems and to evaluate the effects induced by QRS detection errors on the performance of heartbeat classification processing (normal versus abnormal) [30]. An automated patient- specific ECG heartbeat classifier based on an efficient formation of morphological and temporal features from the ECG data and evolutionary NN processing of the input patterns is proposed. The wavelet- based morphology features are extracted from the ECG data and are further reduced to a lower dimensional feature vector using principal component analysis (PCA) technique [31]. Rute Almeida *et al* proposed a novel multilead (ML) based automatic strategy for delineation of ECG boundaries and evaluated with respect to the QRS and T-wave boundaries [32].Within the area of applied Artificial Intelligence (AI), a number of techniques are currently employed in almost every sphere of intelligent computer-based systems. Each technique employs a different emulation of human intelligence and is applied to problems which complement its strengths. The major AI techniques presently in use are: neural networks, genetic algorithms, fuzzy systems and expert systems. Defang Wang et al has developed a method for discretization and refinement strategies involving hybrid shaped finite elements to minimize approximation errors for the ECG inverse problem [33]. Kalman filter with adaptive noise-covariance estimation has been developed and evaluated on a variety of ECG signals to assess whether the filter is capable of enhancing the SNR of these signals, while at the same time preserving clinically relevant morphological variations in the ECG [34]. A new method for flutter wave cancellation in the ECG is developed and validated in order to facilitate the analysis of T wave during atrial flutter [35].

IV. CONCLUSION

Reliable detection of arrhythmias based on digital processing of ECG signals is vital in providing suitable and timely treatment to a cardiac patient. Computerized arrhythmia interpretation systems are very much needed as they aid a cardiologist in taking crucial decisions while diagnosing abnormal heart rhythms. However, due to corruption of ECG signals with multiple frequency noise and presence of multiple arrhythmic events in a cardiac rhythm, computerized interpretation of abnormal ECG rhythms is a challenging task. 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 centres. 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 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. Nonknowledge-based expert systems that are not rule based employ hybrid AI techniques such as fuzzy-neural networks or expert systems using genetic algorithms. Although, hybrid AI systems 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. Such systems are best suited to problems where the expert system intends to make reasoned judgments for huge databases, and to give assistance in a complex area in which human skills are fallible or scarce. Also, uncertainty in ECG classification systems need to be addressed in cases where the signal content is insufficient or the data recording is corrupted by excessive noise; hybrid AI tools may tackle the issues related to uncertainty to a great extent providing efficient solutions.

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AUTHORS PROFILE

Rajiv Ranjan received his B.E. Degree in Electrical Engineering in 2002 from Regional Engineering College (Now, National Institute of Technology), Silchar, Assam and M.Tech. (Electrical) degree in 2009 from Uttar Pradesh Technical University, Lucknow, India. Currently, he is working as an Associate Professor in Department of Electrical and Electronics Engineering Department at Dronacharya Group of Institutions, Greater Noida, U.P., India. His area of interests includes Biomedical Instrumentation, Digital Signal Processing, Power System, Electrical Machines and Instrumentation & Control.

V K Giri obtained his B.E. (Electrical) Degree from REC, Surat (Gujrat) in 1988, M.E. (Measurement and Instrumentation) Hons degree from University of Roorkee, Roorkee in 1997 and Ph.D. degree from Indian Institute of Technology Roorkee, Roorkee in 2003. He joined the Electrical Engineering Department of M.M.M Engineering College, Gorakhpur (UP) in 1989 as lecturer. Presently, he holds the position of Professor in the same department since, 2008. He has published more than 20 research papers, guided 6 PG students; and supervising 3 Ph.D. theses. He has received many awards including the best paper awards of the Institution of Engineers (India) in 23rd Indian Engineering Congress in year 2008. He was elected as Fellow of the Institution of Engineers (I), Institution of Electronics and Telecommunication Engineers, and is a member of many professional bodies such as life member ISTE, member IEE and member CSI. He has also undertaken large number of consultancy, testing & sponsored projects from industries and government departments. His research interests include Digital Signal Processing, Measurement and Instrumentation Biomedical Instrumentation, Data Compression and Telemedicine.