1) Einthoven demonstrated significant differences in normal and abnormal ECG waveforms in 1906 [21] and 1908 [22]. In the experiments to follow, in 1912 [28], Einthoven investigated and found out that the heart creates a potential difference at different locations and the magnitude and direction of the current changes at different locations of the heart can be represented by the Einthoven Triangle is shown in Fig. 7.

He demonstrated that Lead I had advantages for judging the T waves, in Lead II peaks were usually larger and Lead III was most suited for the diagnosis of Ventricular hypertrophy 1 of left and right ventricles. He also observed a linear relationship between the three leads that yielded Lead II − Lead I =

Lead III to obtain any lead by combining the other two leads.

2) Following Einthoven’s invention, scientists became interested in this emerging

field and started categorizing the signals based on their interpretations. Fig.

9 shows the P wave, QRS complex, T wave, J point and Baseline level of the

signal.

Einthoven in 1906 categorized normal and abnormal ECGs that was translated by Cardiologist Henry Blackburn [23]. He discussed the first electrocardiographic tracings of atrial fibrillation 3, premature ventricular contractions 4, ventricular bigeminy 5, atrial flutter 6. The beginning of ECG related research also demonstrated in an experimental setup that induced heart block in a dog, as shown in Fig.10. By then, Thomas Lewis, a physician, was convinced about the significance of Einthoven’s contribution to determine various heart anomalies. Independently, he concluded that atrial fibrillation is a common cause of arrhythmia and termed as a “clinical condition”

4 Abnormal heartbeat where contractions begin in the ventricles, instead of Sinoatrial node of heart

5 Arrhythmia where there is a pattern of irregular heartbeat and regular heartbeat occurrence.

6 Type of arrhythmia, where the heart’s upper chambers (atria) beat too quickly.

Six major categories of anomalies were also coined by Lewis, namely: sinus arrhythmia, heart block, premature contractions, proximal tachycardia, auricular fibrillation and alteration of the pulse. The ECG machine used by Lewis during 1930 to diagnose the patients is shown in Fig. 12. In addition he

also explained the terms such as sino auricular node, pacemaker, premature contractions, proximal tachycardia and auricular fibrillation.

3) In 1934, Frank Wilson defined an ‘indifferent electrode’ that was later

known as ‘Wilson Central Terminal’ by connecting the right arm, left leg and

left arm with resistances typically 5KΩ [39]. Wilson Central Terminal is an artificially constructed reference for electrocardiography, which is assumed to be at zero potential and steady during the cardiac cycle so that the reference

point for unipolar potential remains fixed. It worked as a ground terminal for other unipolar leads. The events that occur during each heartbeat are termed a cardiac cycle that can be divided into two parts: a period of relaxation known as diastole and a period of contraction known as systole. A cardiac cycle on an ECG signal is shown in Fig. 14. In 1938, the American Heart Association and the Cardiac Society of Great Britain published their recommendation for recording the exploring lead from six sites named V1 through V6 across the precordium [39]. Later, Emanuel Goldberger extended the Wilson Central Terminal with Augmented Unipolar Leads (avl,avr and avf ) also known as Goldberger leads

for obtaining a detailed view of the frontal plane [40]. Further, in 1953 the general theory of heart vector projection was presented by Earnst Frank [41] that provided a mathematical framework where three vectors determined the person’s complete cardiac health. This confirmed the robustness of the methods used then with a mathematical validation. In the following year in 1954, the American Heart Association published their recommendation for standardization of 12-lead Electrocardiogram and Vectorcardiogram [42]. Till date, 12

Lead ECG and 3- Lead VCG continues to be the standard of ECG measurement systems.

4) The system consisted of two µcomputers to detect QRS durations for arrhythmias of 24 hours recorded on Holter tapes. It determined the heart rate variability and PVC counts, a method used till date. Around the same year another method of QRS complex detection was presented in [91]. In this method the QRS complex was represented by single positive pulse alongwith onset and end of it, by a dynamic threshold technique by utilizing the time domain features.

A portable µcomputer based Arrhythmia Monitor was designed [92] for storing 16 seconds arrhythmia intervals. The major difference of this system with Holter tapes was that it did not store any normal rhythm data and was advantageous in terms of memory utilization. The system was able to provide continuous and long term monitoring for high-risk patients.

4.5) Following this, Pan and Tompkins proposed the seminal algorithm for QRS detection [104] for normal and abnormal waveforms. This algorithm provided accuracy of more than 99% for QRS detection and revolutionized the means for arrhythmia monitoring. The algorithm also provided the ideal means for heart rate variability measurements that provided real-time processing and reporting various cardiac conditions and diseases.

5) In 1987, another research [105] provided the preliminary heart rate variability (HRV) analysis by using the autoregressive modelling techniques and power spectral density estimates. For the QRS detection, it followed the classical technique by obtaining the derivative of the ECG signal followed by a adaptive thresholding. After obtaining the R-R interval information, it used to discrimate the normal and pathological

subjects by utilizing the autoregressive modelling and power spectral density estimates. In 1988, two methods for detecting the QRS complexes were discussed in [106] based on the length transformation and energy transformation of the signal. In both the methods QRS complexes of the signals were enhanced and other components of the signal were supressed significantly and detection accuracy for QRS complexes were found out be over 99%.

6) Neural networks were first used for ECG signal processing during 1990 for diagnostics [107–113], categorization and QRS detections and proved interesting. The application of neural networks also proved to be advantageous in classifications and detections with extended computations. Over the years, such artificial intelligence algorithms were extended towards categorizing normal and abnormal waveforms and pattern matching. During 1992, detection of QRS complexes for very noisy signals were demonstrated using neural networks [111]. In this work, a multilayer perceptron neural network was used as an adaptive whitening filter instead of a normal linear filter.

6.5) Another work on the QRS template matching was updated by ANN recognition algorithm was discussed in [112]. Several hidden layers in multilayer perceptron with eigenvalue decomposition method to classify the signals available in MIT/BIH database was provided in [113] and the technique was also patient adaptable. Although the neural networks provided better detection accuracy over the conventional classification (based on thresholding and empirical values) but the computations requirements for such systems were high and often difficult to realize on customized hardware

7) authors discussed the utilization of Wavelet Transform (WT) for ECG analysis and it’s compression techniques. The research presented preliminary investigation into its application to the study of both ECG and heart rate variability data. Futher, WTs were also studied independently that provided time and frequency analysis for the ECG signals

Стр 30

The Classification considers the extracted feature points from the previous

stage and classifies the signal into different categories by using empirical, adaptive and constant threshold-based , machine learning-based and Deep Neural

Networks based classifiers. The conventional empirical classifiers are generally based on the medical observations for the particular field. Thresholding based or decision logic-based approach is based on defined logical rules, e.g. R-R interval, ST interval etc.The machine learning-based approaches based on multivariate statistical pattern recognition has a widespread utilization in biomedical signal processing. These methods utilize correlation analysis, regression techniques and template matching to identify abnormal patterns or a particular class of signals [188, 189]. However, as these statistical methods move towards greater accuracy, it also has a higher system complexity. Most recent techniques are

deep neural networks also known as an artificial neural network (ANN) consists of multiple hidden layers between the input and output layers [190]. Each layer consists of neurons with different weights and biases. The neurons can pass the

information to other neurons in other layers. The backpropagation technique provides feedback and updates the weight associated with neurons offering supervised and unsupervised learning. The deep learning technique offers more accuracy to the system at the cost of increased system complexity. Recent developments in deep neural networks is widespread, with the latest techniques discussed in [190] are Recurrent Neural Networks (RNN), Convolution Neural Networks (CNN) and other generative models such as Autoencoders and Generative Adversarial Network (GAN). In the following subsection, various machine learning and neural networks based classifiers for ECG signal processing are discussed.

Стр 30-31-32

5.2.1 Machine Learning and Deep Learning Technique based Classifiers

This section categorizes (shown in Table 6) various researches based on machine learning and deep learning techniques for classification. In [191], authors provided the customized ECG classifier with patient-specific data based on an unsupervised learning technique. The method’s limitation was that it required to develop a local classifier for each patient with patient-specific data. In [192], authors detected the QRS complexes of 12 Lead ECG signal available in CSE dataset -3 with a supervised learning of ANN. The back propagation algorithm has been used to train the system. Authors in [193], utilized the ANN for arrhythmia classification, ischemia detection, and recognition of chronic myocardial diseases. It used both static and a recurrent ANN with preprocessing and postprocessing that defined the dimensions of input features for neural networks. Authors in [194] utilized an unsupervised learning clustering scheme for the classification using Hermite functions based features of QRS complexes. The limitation was that it did not provide signal quality information in the input vector’s self-organizing maps. Authors in [195], used a beat recognition and classifier based on a supervised learning scheme that utilized fuzzy hybrid neural network and higher-order statistics features as inputs. In [196], authors utilized Hermite basis function expansion of the QRS complexes of ECG waveforms and modified Takagi-Sugeno-Kang neurofuzzy network for heartbeat recognition and classification based on a supervised learning scheme. In [197], authors utilized a popular supervised machine learning approach known as Support Vector Machine (SVM) for the recognition purpose. The input features in the method were obtained by two methods namely higher-order statistics (HOS) and Hermite characterization of the QRS complex. In [198], authors classified the ECG data into three categories,

namely normal beat, ventricular ectopic beat(VEB), supraventricular ectopic beat (SVEB). The classification was based on a statistical classifier model utilizing a supervised learning scheme. The limitation was the heartbeat fiducial

points were manually annotated. In [199], authors provided supervised learning based on a decision tree based classifier algorithm to be implemented on apersonal digital assistant (PDA).

In [200], authors used features such as ST segment area, R-S interval, ST-slope, R-T interval, QRS area, Q-T interval, R-wave amplitude, heart beat rate and four statistical features QRS energy, mean of the power spectral density, autocorrelation coefficient,and signal histogram are applied to signal stage and two stage feed forward neural networks for the anomalies detection. In [201], authors used supervised learning that required block based neural networks as classifiers. It utilizes Hermite coefficients and R-R intervals as input features to classify Supraventricular Ectopic beats and ventricular ectopic beats. Authors in [202] utilized the supervised particle swarm optimization (PSO) with the support vector machine classifier on the automatically detected features.