Biomedical Signal Analysis and Its Usage in Healthcare

18

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Abstract

Biomedical signals are collected from a body that can be at the organ level, cell level, or molecular level. There are different biomedical signals including the electroencephalogram (EEG), which is the electrical activity from the brain; the electrocardiogram (ECG), which is the electrical activity from the heart; the electromyogram (EMG), which is the electrical activity from the muscle sound signals; the electroneurogram; the electroretinogram from the eye; and so on (Muthuswamy, Biomedical signal analysis. In: Myer Kutz (ed) Standard handbook of biomedical engineering and design, vol 14. McGraw-Hill Education, New York, pp 1–18. 2004). Biomedical signals are primarily used to diagnose or detect specific pathological or physiological conditions. Additionally, these signals are employed to analyze biological systems in the healthcare. The aims of signal processing are signal denoising, precise recognition of signal model through analysis, feature extraction and dimension reduction for decisive function or dysfunction, and prediction of future functional or pathological events by employing machine learning techniques. The objective of this chapter is to present how biomedical signals are used in the healthcare and what are the steps of biomedical signal analysis.

Keywords

Electrocardiograms (ECG) · Electroencephalograms (EEG) · Electromyograms (EMG)

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18.1 Introduction

Biomedical signals are acquired from a medical or biological source which can be at the cell level, molecular level, or organ level. Several biomedical signals are generally employed in the research laboratory, clinic, and occasionally even at home. The electroencephalogram (EEG), or electrical activity from the brain or electrical responses of the brain to specific peripheral stimulation; the electrocardiogram (ECG), or electrical activity from the heart; the electromyogram (EMG), or electrical activity from the muscle; the electroretinogram from the eye; the electroneurogram, or field potentials from local regions in the brain; and so on are the widely known examples of the biomedical signals. In clinics, biomedical signals are mainly recorded to detect definite physiological or pathological conditions and diagnose and evaluate the therapy. Biomedical signal analysis is employed to remove the noise, create accurate signal model and analyze its components, extract features for decisive function or dysfunction, and predict future pathological or functional events in brain, heart, or muscle (Muthuswamy 2004). Biomedical signals contain information which is beneficial for understanding of the complex pathophysiologic mechanisms and behavior of living systems. However, such information may not be obtainable directly from the raw signals which might be disguised by other biomedical signals sensed or suppressed in additive noise. Because of these reasons, biomedical signal processing is generally needed to improve the related information and to describe the level of pathology for routine clinical diagnosis, rehabilitation, or therapy. Numerous signal processing approaches, which are sometimes termed as preprocessing techniques, can be employed for these purposes such as denoising, averaging, filtering, spectral estimation, and feature extraction. Biomedical signals are collected from sensors, electrodes, or transducers and then transmitted, stored, and treated (Mainardi et al. 2006).

Biomedical signals collected from the body deliver information related to the organs. Their spectral and temporal specifications might be associated with pathological or normal conditions. According to temporal variations in the function of the organs, the biomedical signals may show nonstationary as well as time-varying characteristics. Time-frequency analysis methods, such as wavelet, are more suitable for biomedical signals analysis. These methods are used for the analysis of time-varying and transient events in biomedical signals including cardiac and neurological signals. Biomedical signal processing utilizes complex mathematical techniques to achieve information hidden in the signals recorded from sensors. In biomedical engineering, these sensors and electrodes collect signals from biological tissue to check their well-being and health in clinical environment. Hence biomedical signal processing techniques needs employing appropriate signal modelling to extract features which is important for diagnosis. Since most of the biomedical signals are time-varying, it is essential to capture transient phenomena in both abnormal and healthy states. A crucial characteristic of several biomedical signals is the frequency domain feature. Similarly, biomedical signal pattern represents the transition from simple normative to unhealthy states of an organism occasionally undertaking severe variations that can be easily distinguished utilizing time-frequency methods such as wavelet transform. Biomedical signals are generally spread out over wide range of the frequency spectrum, the frequency content of a biomedical signal varies quickly as in the case of the heartbeat fibrillating in an ECG and seizure spikes in epilepsy. Wavelet transform, which has wideband representation of signals, is a usual choice in biomedical signal processing (Thakor et al. 2000).

The focus of this chapter is to support the biomedical researcher in order to choose the suitable representation or study of the biomedical signal from the existing models and then guide the engineer toward an ideal approach for enumeration. Hence, this chapter discusses the usage of basic biomedical signals (ECG, EEG, and EMG) in healthcare and techniques for analyzing them employing fundamental signal-processing and classification methods which find widespread application in biomedical signal analysis.

18.2 Biomedical Signals

18.2.1 The Electrocardiogram (ECG)

The electrocardiogram (ECG) signals are electrical activities originated from heart on the body surface so that isopotential surfaces can be calculated and analyzed over time. The contemporary ECG device is entirely combined with an analog front end, an analog-to-digital (A/D) converter, dedicated input-output (I/O) processors, and a microcomputer. The better hospital-based system can collect these changes and keep an ECG database which includes the permutation of parameters, e.g., all females, elder than age 30, with an inferior congenital heart disease. There are hundreds of demonstrative approaches where a particular diagnosis is completed for every ECG, but there are only five or six main classification sets for which the ECG is employed. The initial step in ECG analysis needs computation of the rhythm and rate for the atria and ventricles. This includes whichever conduction instability either in the connection among the different chambers or within the chambers themselves. Then feature identification that would be connected to the absence or existence of damaging because of the myocardial infarction would be done (Berbari 2000; Subasi 2019).

The heart consists of four chambers; the lower two chambers are named as ventricles and the upper two chambers are named as atria. The atria collect blood from the venous circulation. Positioned in the upper right atrium are a group of cells that operate as the main pacemaker of the heart. The nature of the body surface waves is dependent on the total of tissue activating at one time and the relative speed and direction of the activation wave front. Thus, the pacemaker potentials that are produced by a tiny tissue mass are not visible on the ECG. As the activation wave front faces the amplified mass of atrial muscle, the beginning of electrical activity is noticed on the body surface, and the initial ECG wave of the cardiac cycle is visible (Berbari 2000). The heart is one of the main organs of the human body, crucial to our existence. It is basically a huge pump, with only function is to keep blood circulation and preserve organs alive (Begg et al. 2008; Subasi 2019).

The QRS complex is an electrical ventricular system and the most well-known waveform showing electrical activity inside the heart. It is the basis for automatic recognition of heart rate and also as an access point for classification schemes. The QRS complex morphology describes the mechanical action of the heart offering a view into how each chamber is functioning. The waves of depolarization extending all the way through the heart via each cardiac cycle produce electrical impulses. These impulses travel via a variety of body fluids, e.g., blood, up to the body's surface where they can be recorded using surface electrodes. These signals are then sent to an electrocardiograph. The main characteristics of the QRS wave that describe significant data related to cardiac health are as follows (Begg et al. 2008; Subasi 2019).

(a) P wave
(b) QRS complex
(c) T wave
(d) QRS intervals.

There are different heart arrhythmias. In this chapter, four major heart arrhythmias are selected because these are most frequent arrhythmias. These are premature ventricular contraction (PVC), atrial premature contraction (APC), right bundle branch block (RBBB), and left bundle branch block (LBBB). In the following text, it will be given short description of these four arrhythmias (Jones 2008).

Many researchers studied on biomedical signal analysis and machine learning techniques for computer aided diagnosis (CAD) using ECG signals. Earlier researches done in this field suggest that biomedical signals taken from complex systems under healthy conditions may have a fractal temporal structure (Bassingthwaighte et al. 2013). Many researches (Muller et al. 1992; Lai and Chan 1998; Esgiar and Chakravorty 2004) presented that ECG signals are proper models as self-affined fractal sets and it is realizable to perform accurate classification by using fractal dimension. Recently, variety of detection algorithms have been proposed. Thakor et al. (1990) proposed the sequential hypothesis testing; the threshold-crossing intervals, the auto-correlation function and the VF-filter were suggested by Clayton et al. (1993), and algorithms based on neural-networks were suggested by Yang et al. (1994).

ECG based CAD systems contains two functional parts: feature extraction and classification. There are different ways for feature extraction. In (de Chazal and Reilly 2003; Hu et al. 1997; Moraes et al. 2002), feature extraction was done in time domain. In Acharya et al. (2004) and Minami et al. (1999), feature extraction was done in frequency domain. Al-Fahoum and Howitt (1999) extracted features by using multiscale decomposition. Osowski and Linh (2001) used statistical measures for feature extraction. A lot of work has also been dedicated to the improvement of classification techniques for these feature sets, such as linear discrimination, decision trees, neural networks, and the combination of experts systems (Yu and Chou 2007).

There are also numerous works done reporting the use of multifractal model for cardiac signal analysis (Ivanov et al. 1999; Wang et al. 2007). Raghav and Mishra

(2008) tried to use local fractal dimension based on nearest neighbor classification algorithm for ECG signal-based heart disorders, and results achieved were promising (A. K. Mishra and Raghav 2010). Qin et al. (2005) used radial basis function neural network (RBFNN) to classify ECG signals. Different neural network techniques were used such as techniques suggested in (Prasad and Sahambi 2003; Yu and Chou 2008; Yong et al. 2009; Nadal and de Bossan 1993) were used for ECG signal classification. Classification has also been performed using support vector machines (Acır 2006; Asl et al. 2008; Besrour et al. 2008; Melgani and Bazi 2008). Other works were conducted using genetic algorithms (Kutlu and Kuntalp 2011). Özbay et al. (2006) suggested fuzzy logic classification tool. k-nearest neighbor (k-NN) classification tool was used in Arif et al. (2009), Karimifard et al. (2006), Christov et al. (2005), and Arif and Akram (2010).

During ECG recording, several sources can add noise to the acquired signal. Imperative noise sources can be electrical power line interference, noise due to instrumentation or electronic devices, impedance changes at the skin/electrode edge, movement artifacts such as electrode movement, baseline drifts caused by respiration, and electrosurgical noise. Thus, precise preprocessing of the ECG signals is crucial to reduce the variety of noise components and enhance the signal-to-noise ratio (SNR) meaningfully. Consequently, a single band-pass filter having 10–25 Hz pass-band is utilized for the ECG signal filtering (Begg et al. 2008). Since ECG signal denoising and feature extraction present an indication about several cardiac abnormalities for diagnosis of cardiovascular disorders, it received lot of attention from the medical societies. Alickovic and Subasi (2015) denoised ECG signals using multiscale PCA (MSPCA) for arrhythmia detection. To achieve a better classification performance, noise should be removed. The proposed framework demonstrated that MSPCA denoising increases the classification accuracy. Moreover, Alickovic and Subasi (2016) proposed another framework where MSPCA was utilized for denoising, DWT for feature extraction, and random forest classifier for ECG signal classification, and they achieved higher accuracy. Usta and Yildiz (2017) employed random forests (RF) classifier to classify heart arrhythmia using ECG signals.

Afkhami et al. (2016) used MIT-BIH arrhythmia database including several forms of common arrhythmias. Dual tree complex wavelet transform based feature extraction technique is proposed by Thomas et al. (2015) for automatic classification of cardiac arrhythmias. The results showed that dual tree complex wavelet transform (DTCWT)-based feature extraction technique achieved better accuracy than discrete wavelet transform (DWT) for five types of ECG beats of MIT-BIH arrhythmia database. Li and Zhou (2016) utilized statistical features extracted from DWT, ICA for dimension reduction, and PNN, k-NN, DT, and SVM for classification. Li and Zhou (2016) proposed a method to classify ECG signals using wavelet packet entropy and random forest. Cruz et al. (2016) employed DWT in ECG signal classification and compared support vector machine (SVM) and adaptive neuro-fuzzy inference system (ANFIS). The experimental result showed that SVM achieved better performance in terms of sensitivity, specificity, accuracy, and training time, while ANFIS had the fastest evaluating time. H. Li et al. (2016) proposed a new framework for classification ECG signals by combining WPD and ApEn for feature extraction and LIBSVM for classification. The algorithm utilizes the PSO to determine the best parameters. Ai et al. (2015) used GND-ICA feature-fusion method based on a multilearning subspace-learning algorithm for ECG heartbeat classification by utilizing MIT-BIH arrhythmia database in all experiments (Subasi 2019).

KalaiSelvi et al. (n.d.) utilized DTCWT-based feature set for classifying ECG beats. The performance of the developed technique is compared with DWT feature extraction and it is realized that the proposed feature set was achieved higher recognition performance than the DWT based feature set. Kiranyaz et al. (2015) discussed the classification of ECG heartbeat is used CNN to record and detect the heart problem. The approaches are given maintaining a robust fast, and patient-specific scheme with a superior classification performance of the heart problem. Qurraie and Afkhami (2017) developed a novel algorithm based on the TF to get the features and the decision tree for the arrhythmia classification (Subasi 2019).

18.2.2 The Electroencephalogram (EEG)

Electrical signals produced by the brain characterize the brain function and the status of the whole body. This delivers the motivation to utilize biomedical signal processing techniques to the electroencephalogram (EEG) signals acquired from the brain of a human subject. The physiological characteristics of brain activities have numerous issues regarding to the characteristics of the original sources and medium and their actual patterns. The medium describes the path from the neurons, that are signal sources, to the electrodes, that are the sensors in which some form of mixtures of the sources are collected. Understanding of neurophysiological properties and neuronal functions of the brain together with the working principle underlying the signal generation and acquisition is useful when dealing with these signals for recognition, analysis, and treatment of brain disorders. EEG presents the way of diagnosis of several neurological disorders and abnormalities in the human body (Sörnmo and Laguna 2005; Subasi 2019).

Electroencephalograms (EEGs) are recordings of the electrical potentials created by the brain, usually less than 300 μV. EEG has been conducted mostly in research facilities and medical settings with the aim of detecting pathologies and epilepsies. An electroencephalographer, an individual trained to qualitatively differentiate normal and abnormal EEG activity within pretty long EEG records, was for many years the only person qualified for visual interpretation of the EEG. Therefore, researchers and clinicians were left and covered up in a bunch of EEG paper records. However, the arrival of modern powerful computers and related technologies opened a whole new door of possibilities for applying various methods to quantify EEG signals (Bronzino 1999; Subasi 2019).

Even though the EEG has lost portion of its supremacy in medical routine due to these modalities, it still remains a very powerful tool for the analysis of many diseases like epilepsy, sleep disorders and dementia. Moreover, the EEG signal is essential for real-time monitoring of progress of patients with encephalopathies or the ones in a coma. In these applications, the temporal resolution of the EEG is unmatched by the imaging. Furthermore, the overall cost related with recording equipment and skilled workers required for managing the instrumentation is significantly lower than the cost related with neuroimaging. For a simple recording system, the technical demands on instrumentation are quite modest. They are limited to a set of electrodes, a signal amplifier and a PC for data storage, signal analysis and graphical demonstration (Sörnmo and Laguna 2005; Subasi 2019).

The EEG signal from the scalp has time duration of 0.01–2 s and amplitude of around 100 μV (Kerem and Geva 2017). The frequency components of the EEG signals are generally employed for the analysis taking into account of the following frequency bands: Delta (up to 4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–26 Hz), and Gamma (26–100 Hz). Waveform activities differs from each other according to the brain function related to the mental and physical tasks. For instance, low-frequency waves (delta and theta) dominate during sleep times, while an EEG signal acquired during awake times includes a higher percentage of high-frequency waves (alpha and beta). Also, transition from an eyes open state to an eyes closed state changes the EEG frequency spectrum; the state with closed eyes has a diverse peak in the spectrum around 10 Hz (Felzer and Freisieben 2003). The EEG signals are semi-stationary time-dependent and non-stationarity in the waveforms. Hence, these characteristics cannot be detected easily. Power spectrum achieves a quantitative measure of the frequency distribution of the EEG at a cost of the amplitude distribution and information related to the existence of EEG patterns. Even though, these primary efforts are unsatisfactory, they allow the use of frequency analysis in the analysis of brain wave activity. Therefore, time-frequency methods such as wavelets are applied for feature extraction from the EEG signal (Bigan 1998). Furthermore time-frequency methods such as discrete wavelet transform (DWT), wavelet packed transform (WPT), tunable Q wavelet transform (TQWT), dual tree complex wavelet transform (DTCWT), empirical wavelet transform (EWT), and empirical mode decomposition (EMD) are essential to explain the different behavior of the EEG to express it in both the time and frequency domain. It should also be highlighted that the wavelet is appropriate for the analysis of nonstationary signals such as EEG, ECG, and EMG. Therefore, the wavelet is appropriate for detecting transient events, such as spikes occur during epileptic seizures (Bronzino 2000; Adeli et al. 2007; Subasi 2007; Subasi and Gursoy 2010).

The lack of clear difference in EEG activities makes the visual detection of different disorders from EEG signals challenging (Bigan 1998). Therefore, computer aided decision support systems were developed to allow more precise and quicker detection of disorders from the EEG recordings. ANN-based classifiers' performance was compared in Pang et al. (2003). They trained ANN with features selected from a raw EEG signal. A system for the automatic analysis and detection of epileptic seizures using wavelet transform to extract features from EEG signals was developed by Bigan (1998). An ANN model was used for the automated analysis of the EEG recordings. A discrete wavelet transform (DWT) and a mixture of expert model were employed for EEG signal classification in (Subasi 2007).

In Subasi and Gursoy (2010), DWT was used for feature extraction; PCA, ICA, and LDA were used for dimension reduction; and support vector machines (SVM) is used for the classification of EEG signals. Subasi et al. (2017) proposed an epileptic seizure detection model to determine the optimum parameters of support vector machines (SVMs) by employing particle swarm optimization (PSO) and genetic algorithm (GA). Alickovic et al. (2018) compared wavelet packet decomposition (WPD), discrete wavelet transform (DWT), and empirical mode decomposition (EMD) for epileptic seizure detection and seizure prediction. Soleimani et al. (2012) proposed a robust technique to elaborate and evolve a neuro-fuzzy model which works as an online adaptive method with a patient-independent parameter for a seizure prediction. Furthermore, prediction is improved by using multiple features to detect the preictal patterns. Liu et al. (2012) proposed wavelet decomposition of multichannel intracranial EEG (iEEG) within five scales by selecting three frequency bands. They extracted effective features such as relative amplitude, relative energy, and coefficient of variation and fluctuation index at particular scales. SVM is employed for classification and achieved low false detection rate and high sensitivity for seizure detection in long-term iEEG. Williamson et al. (2012) combined multivariate EEG features with patient-specific machine learning for seizure prediction. The proposed algorithm calculates the covariance matrices and eigenspectral of space-delay correlation from EEG data and classifies the data using support vector machine. Aarabi and He (2012) implemented a rule-based patient-specific seizure prediction framework for focal epilepsy. They used five univariate measures, including largest Lyapunov exponent, Lempel-Ziv complexity, correlation entropy, correlation dimension, and noise level as well as one bivariate measure, nonlinear interdependence which are extracted from electrodes implanted deep in the brain.

18.2.3 The Electromyogram (EMG)

The duty of human skeletal muscular system is to achieve the forces required to carry out a several activities. Such system composed of the nervous system and the muscular system, together creating the neuromuscular system (Begg et al. 2008). Motion and arrangement of limbs are administered by electrical signals propagating back and forth among the muscles and the peripheral and central nervous system (Bronzino 1999). The central nervous system (CNS) administers via nerve signals and muscles excitation. The skeletal-muscular system is composed of muscle sets connected to bones via tendons and a motion is done once nerve signals produce muscle contractions and relaxations that either attract or repel the bone (Begg et al. 2008).

Neuromuscular disorders consist of abnormalities initially appearing in the nervous system, in the neuromuscular junctions, and in the muscle fibers. These abnormalities have distinct degrees of severity going from negligible damages of muscle to amputation caused by neuron or muscle death. In more severe disorder like amyotrophic lateral sclerosis (ALS), decease is generally assured. In the majority of cases, clinical testing is insufficient to detect and prevent disorder from spreading

(Preston and Shapiro 2012) since a lot of dissimilar abnormalities could be results a specific symptom. Correct diagnosis of the disorder is, for that reason, of supreme significance so as result more purposeful healing can be done employing electromyography (EMG) that was first used as a method of evaluating neuromuscular states established on cell action capabilities throughout muscle activity. The understanding of EMG is as a rule done by trained and expert neurologists who besides examining EMG waveforms employ methods such as needle conduction researches and muscle acoustics as well. Trouble appears once there are too hardly any specialists to assemble the demand of patients and, consequently, it is imperative to build up automated diagnostic systems established on EMG readings. This offers range for the usage of machine learning methods for the discovery and classification of neuromuscular irregularities based on EMG processing. These smart systems will help doctors in discovery of abnormalities in the neuromuscular system. The goal of smart diagnostic and artificially administered neuromuscular systems is to primary preprocess the raw EMG signal and after that take out characteristic data or features that may be taken out comprising of time and frequency domain data. This data may after that be employed as input data for classifiers that may classify neuromuscular disorders. The challenge in this case is to invent signal-processing method that protect or confine significant discriminatory data so as to give a good quality set of features for classification. Neuromuscular disorders are anomalies related to the peripheral nervous system. They can be classified based on the location and reason of the disorders. Two main disorders are neuropathy and myopathy. Neuropathy is a disease about nerves that cause the pain and some disability. The causes of neuropathic disorders are injury, alcohol abuse, infection, diabetes, and cancer chemotherapy. It can be categorized as mononeuropathy and polyneuropathy. Myopathy is a disorder generally related with the skeletal muscle that caused by injury of a muscle group or some genetic mutation. The patient suffering with myopathic diseases has week muscles and depending on severity of disorder, has problem with the performing regular task or impossible to make any movement by using effected muscles (Begg et al. 2008; Subasi 2019).

A number of researches have been done to design an accurate automated diagnosis system by employing different classification algorithm to classify EMG signals (Richfield et al. 1981; Subasi et al. 2006). It is possible to find commercial version of some algorithm on the market, but almost none of them are used at clinics to diagnosis of the neuromuscular disorders (Bozkurt et al. 2016). Autoregressive (AR) analysis and time domain analysis were used together to classify the EMG signals by Pattichis and Elia (1999). De Michele et al. (2003) applied the wavelet cross-correlation analysis on the two different muscle and find out that it is possible to make detailed classification. MUAP parameters were used as input to the parametric sequential pattern recognition classifiers by Pattichis et al. (1995). Loudon et al. (1992) used eight different MUAP parameters as input to the statistical pattern recognition techniques to classify the EMG data. Hassoun et al. (1994a, b) applied the time domain parameters as input to a tree-layered ANN and used “Pseudo Unsupervised” algorithm as classifier in their study. Two different classification methods were used at the same time to classify the EMG signals by

Christodoulou and Pattichis (1999). They proposed to use unsupervised machine learning algorithms, including self-organized feature maps, learning vector, and Euclidian distance. Genetic algorithms were used to classify EMG signals by Schizas and Pattichis (1997). Recent years, wavelet neural network (WNN) was used to analyze the EMG signals. Subasi et al. (2006) used AR signal processing with WNN to classify EMG data. They stated that they classify the EMG signals with the accuracy of 90.07% and it is possible to develop a simple, accurate, and reliable enough automated classification system for routine clinical usage. Katsis et al. (2006) used SVM to classify the EMG data. The features of EMG signals were extracted by wavelet method and used as input to ANN algorithm and learning vector quantization (LVQ) by Guo et al. (2006). Jiang et al. (2006) performed the wavelet transformation of EMG signals and then used the statistical characteristic of wavelet coefficients as input to an ANN. By using similar techniques, Cai et al. (1999) extracted feature vectors by using wavelet transform and used them as input to an ANN which was trained by a standard backpropagation algorithm to classify the EMG signals.

EMG presents a comprehensive information to describe neuromuscular activity and muscular morphology. The EMG signals must be decomposed, classified, and analyzed in order to describe a muscle using quantitative EMG (QEMG) data. In order to diagnose neuromuscular disorders, EMG signal must be classified for the detection of abnormalities (Yousefi and Hamilton-Wright 2014). Recently, Rasheed et al. (2008) developed a model to distinguish individual MUP waveforms from a raw EMG signal to extract relevant features, and classify the MUPs. The adaptive fuzzy k-NN classifier with time domain features and with wavelet domain features are presented. EMG signal are segmented utilizing threshold technique to identify possible MUAPs. Statistical pattern recognition technique is utilized for clustering the identified MUAPs. After employing autoregressive (AR) method for feature extraction, MUAPs are classified utilizing binary support vector machine (SVM) classifier (Kaur et al. 2010).

Subasi (2012a) utilized several feature extraction methods and machine learning techniques such as multilayer perceptron neural networks (MLPNN), dynamic fuzzy neural network (DFNN), and adaptive neuro-fuzzy inference system (ANFIS) to classify the EMG signals and compared them according to their accuracy. In the proposed framework, neuro-fuzzy classification methods were capable to classify the EMG signals with the high accuracy. Moreover, Subasi (2012b) developed an effective combination of classifier and features to classify the EMG signals. LDA, RBFN, MLPNN, C4.5 DT, SVM, and Fuzzy SVM classifiers are used with statistical features extracted from DWT sub-bands. It is reported that the FSVM and the statistical features extracted from DWT sub-bands utilizing the internal cross validation method achieved a better performance than other classifiers. Subasi (2013) proposed a framework in which DWT is utilized to decompose the EMG signals into the frequency sub-bands and then a set of statistical features were extracted from these sub-bands. Substantial improvements in terms of classification accuracy was realized by the developed PSO-SVM classification system. Furthermore, Subasi (2015) used an evolutionary approach to classify EMG signals utilizing SVM classifier and the frequency sub-bands of DWT. A comparison research was done between combined neural network (CNN) and feedforward error backpropagation ANN (FEBANN) classifiers by Bozkurt et al. (2016).

Gokgoz and Subasi (2014) studied the effect of multiscale principal component analysis (MSPCA) denoising in EMG signal classification. Multiple signal classification (MUSIC) processing technique was utilized for feature extraction to classify EMG signals into normal, ALS, or myopathic. It was realized that MSPCA denoising was improved the classification accuracy. After denoising EMG signals with MSPCA, the classification accuracy was 92.55% for SVM, 90.02% for ANN, and 82.11% for k-NN. The same researchers (Gokgoz and Subasi 2015) presented a framework for classification of EMG signals utilizing decision tree algorithms for classification, DWT for feature extraction, and MSPCA for denoising. Parsaei and Stashuk (2013) employed the k-means clustering, and the supervised classification is realized by utilizing a certainty-based algorithm. Dobrowolski et al. (2012) used the wavelet index to classify myopathic, neuropathic, or normal EMG signals. Kamali et al. (2013) proposed a scheme which utilizes both time and time-frequency features of a MUAP along with an ensemble of SVM classifiers. Time-frequency features are DWT coefficients of the MUAP. Time domain features consist of peak to peak amplitude, turn, area, duration and phase of the MUAP. Kamali et al. (2014) employed ensemble of support vector machines (SVMs) classifiers to determine the class label (myopathic, neuropathic, or normal) using both time domain and time-frequency domain features of the EMG signal.

Artameeyanant et al. (2016) proposed a normalized weight vertical visibility algorithm as a feature extraction method for ALS and myopathy detection. In the proposed method, the features are extracted by utilizing selective statistical mechanics and measurements, and the extracted features are used as a feature matrix for classifier input. Finally, powerful classifiers, such as multilayer perceptron neural network, support vector machine, and k-nearest neighbor classifiers are employed to categorize signals into healthy, ALS, and myopathy. Naik et al. (2016) presented a classification technique for neuromuscular disorders (myopathic, and ALS) which utilized a single-channel EMG sensor. The single-channel EMG signals are decomposed by employing ensemble empirical mode decomposition algorithm, then the FastICA algorithm is used for dimension reduction. A reduced set of features are classified utilizing the linear discriminant analysis, and the classification results are fine-tuned with a majority voting scheme. Khan et al. (2016) proposed a framework that utilizes both time domain and time-frequency domain features extracted from the EMG signals. Several classification approaches including single classifier and multiple classifiers with time domain and time-frequency domain features were examined. SVM and k-NN classifiers are employed to predict class label (Normal, Neuropathic, or Myopathic). Sengur et al. (2017) proposed a deep learning based classifier for effectively categorization of normal and ALS EMG signals. They used different time-frequency methods combined with convolutional neural network for EMG signal classification. Mishra et al. (2017) employed improved empirical mode decomposition (IEMD) in combination with the least squares support vector machine (LS-SVM) classifier is used for the analysis of

ALS and normal EMG signals. The proposed technique is achieved 96.33% accuracy. Hazarika et al. (2018) presented a real-time feature extraction and fusion model for an automated classification of electromyogram signals with amyotrophic lateral sclerosis (ALS), myopathy (MYO) and normal (NOR) using Discrete wavelet transform and canonical correlation analysis (CCA).

18.3 Biomedical Signal Analysis Framework

The general framework for the biomedical signal analysis is shown in Fig. 18.1. This framework includes three main modules: (1) signal preprocessing/denoising, (2) feature extraction/dimension reduction, and (3) classification. In this section, comprehensive explanation of each module will be provided.

18.3.1 Biomedical Signal Denoising

The biomedical signals contain several types of artifacts including internal or external interfering noises. These artifacts can be eliminated by employing signal denoising techniques to filter out most of the artifacts and noise (Sanei 2013). The biomedical signal analysis and processing are implemented in three main steps: preprocessing/denoising, feature extraction/dimension reduction, and detection/classification. The main goal of preprocessing is to simplify succeeding procedures without losing related information and to enhance the signal quality by increasing the signal-to-noise ratio (SNR). Filters and transformations such as ICA, PCA, KPCA, and MSPCA are often used during preprocessing. Researchers employ these methods to eliminate or at least reduce the unwanted signal components by transforming the signals. The capacity of PCA can be combined with the ability of wavelet analysis to form multiscale principal component analysis (MSPCA) in order

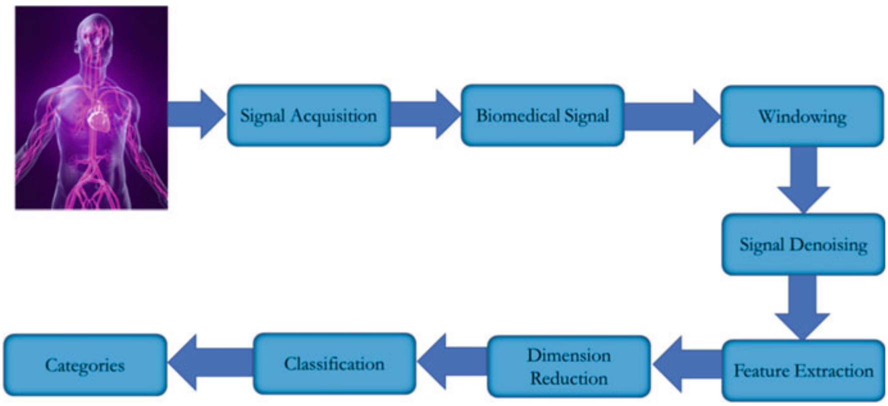

Fig. 18.1 General biomedical signal analysis framework

to eliminate the relationship among the variables with the ability of wavelet transform to extract features and to remove the relationship between auto-correlated measurements. The PCA of the wavelet coefficients at every scale is calculated by MSPCA with integrating the results at relevant scales. MSPCA is efficient since it includes contributions of events of which behaviors become different over time and frequency (Bakshi 1998).

The MSPCA denoising technique can be realized in three main steps. All signals from X_{nxm} is decomposed using wavelet in the initial step. Then, for each wavelet decomposition level, PCA denoising algorithm is applied separately, and wavelet coefficients that have certain threshold value are kept. In the last step, the PCA application for all levels are combined, to get a denoised input signal matrix $\dot{X}_{nxm}$ (Bakshi 1998). The MSPCA shows better denoising performance than PCA algorithm (Kevric and Subasi 2017).

18.3.2 Feature Extraction

One of the crucial steps in the biomedical signal analysis is the feature extraction. Therefore, the biomedical signals composed of several data points, and informative features can be extracted by using different feature extraction methods. These distinctive and informative parameters describe the behavior of the signal waveform which specify a precise action. The biomedical signal patterns can be represented by frequencies and amplitudes. These features can be extracted using different feature extraction algorithms which is another step in signal processing to simplify the succeeding stage for classification (Graimann et al. 2009). The biomedical signals can be decomposed using time-frequency (TF) methods which can detect changes in both time and frequency (Sanei 2013). It is important to deal with a smaller number of values that characterize proper features of the signals to accomplish better performance. Features are generally collected into a feature vector by transforming signals into a relevant feature vector known as feature extraction. Distinctive features of a signal are analyzed by a signal classification framework, and depending on those distinctive features, class of the signal is decided (Siuly et al. 2016). Time-frequency methods, such as Wigner-Ville transform, short-time Fourier transform (STFT), wavelet transform (WT), discrete wavelet transform (DWT), wavelet packet transform (WPT), tunable Q-factor wavelet transform (TQWT), dual tree complex wavelet transform (DTCWT), empirical mode decomposition (EMD), and ensemble EMD, decompose signals in both time and frequency domain.

The wavelet transform (WT) is a time-frequency signal decomposition algorithm on a set of orthogonal basis functions taken by contractions, dilations, and shifts of a mother wavelet. WT, which achieves a good time resolution for high-frequency components and good frequency resolution for low-frequency components, has been employed broadly for biomedical signal processing (Muthuswamy 2004). The continuous wavelet transform is denoted as

$$W_x(u,s) = \frac{1}{\sqrt{S}} \int_{-\infty}^{+\infty} x(t)\psi^*((t-u)/s)\,\mathrm{d}t \tag{18.1}$$

The orthogonal basis functions can be taken by scaling and shifting a *mother wavelet* function ψ(t)

$$\psi_{\mathrm{mk}}(\mathrm{t}) = 2^{-\mathrm{m}/2}\psi(2^{-\mathrm{m}}\mathrm{t} - \mathrm{k}) \tag{18.2}$$

In the discrete TFRs both time and scale variations are discrete. Scaling for the DWT includes sampling rate changes. A larger time band is enclosed for a larger scale for a given number of samples. Naturally, a binary or dyadic scaling structure is used so that given a discrete wavelet function, $\psi(x)$, is scaled by values that are binary. Hence

$$\psi 2^{\mathrm{j}}(\mathrm{t}) = 2^{\mathrm{j}}\psi(2^{\mathrm{j}}\mathrm{t}) \tag{18.3}$$

where j is the scaling index and $j = 0, -1, -2, \ldots$. In a dyadic scheme, subsampling is always decimation in-time by a power of 2. Translations in time will be correspondingly larger as well as for a more sizable scale. Once the scale is enlarged, resolution is lowered. Resolution mainly corresponds to the frequency. Signals are decomposed into a series of orthogonal wavelets in a way that every orthogonal vector space represent signal components with varying levels of scale and resolution. Mallat (1989) called this algorithm *multiresolution signal decomposition*. In every step of the algorithm, wavelets are generated with successively finer depictions of signal content. In order to produce an orthogonal wavelet depiction, a given wavelet function is first dilated by the scale coefficient 2^{j}, then translated by $2^{-\mathrm{jn}}$ (Thakor et al. 2000). This process is shown in Fig. 18.2.

The application of DWT as a feature extraction from the biomedical signals will be given in sect. 18.4.

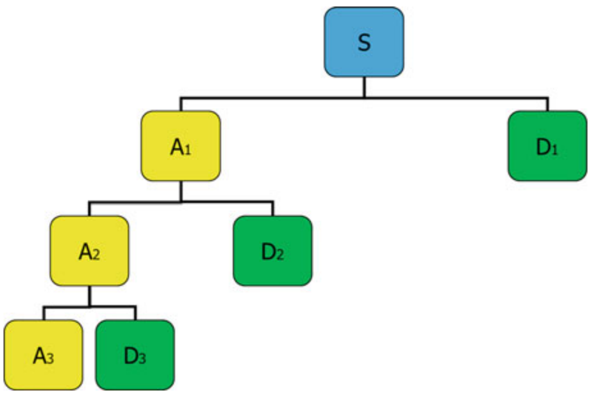

Fig. 18.2 DWT for scale level 3

18.3.3 Dimension Reduction

Dimension reduction is a process to decrease the dimension of the original feature vector, while keeping the most distinctive information and removing the unrelated information (Phinyomark et al. 2013). Most of the feature extraction methods yield redundant features. Actually, in order to improve the performance of a classifier and achieve minimum classification error, some types of feature selection/reduction methods that produce a new set of features must be applied. Several methods employed for dimension reduction and feature selection to achieve better a classification accuracy (Wołczowski and Zdunek 2017).

The dimension of biomedical signals should be reduced to analyze the data for achieving more accurate results. Small number of parameters are employed to reduce the dimension of the biomedical signals through different ways. Furthermore, the features or dimensions must be minimized for achieving better classification accuracy. For example, the DWT produces wavelet coefficients to describe the signal energy distribution in both time and frequency domains and they describe the biomedical signals with set of wavelet coefficients. Meanwhile, wavelet-based feature extraction methods yield the feature vector that are too big in size to be employed as an input to a classifier, a dimension reduction method should be utilized to achieve a smaller number of features from wavelet coefficients. Recently various dimension reduction methods such as Lyapunov exponents, higher order statistics, and entropies have been employed for dimension reduction. First, second, third and fourth order statistics of the sub-bands of the wavelet decomposition can be employed for reducing dimension. The six statistical features are utilized for the biomedical signal classification which are:

1. Mean absolute values of the signal coefficients in every sub-band,
2. Average power of the signal coefficients in every sub-band,
3. Standard deviation of the signal coefficients in every sub-band,
4. Ratio of the absolute mean values of signal coefficients of adjacent sub-bands,
5. Skewness of the signal coefficients in every sub-band,
6. Kurtosis of the signal coefficients in every sub-band.

18.3.4 Machine Learning Methods

Machine learning algorithms utilized to optimize a performance criterion using historical data or learned experience. The model defined with system parameters designed and controlled with hyperparameters, and learning is the optimization of the parameters by the execution of a machine learning algorithm to search the optimal parameters using the training data, which are historical data or previously acquired experience. The main learning goal can be predictive to make forecasts from the labeled data such as classification and regression models. Machine learning algorithms mainly utilize the theory of statistics in designing models, because the aim is to describe the samples or make an inference from the samples. In order to develop machine learning models, in training, you need to consider the performance by means of accuracy to find a solution for the optimization problem. Moreover, once a model is trained, its representation and soft computing solution for learning inference need to be efficient by means of space and time complexity as well. In certain applications, efficiency has also great importance, for example, efficiency is often as much as important as accuracy for the data mining applications. In medicine, learning programs are used for disease identification and diagnosis (Alpaydin 2014).

18.4 Biomedical Signal Analysis Applications

In order to get a consistent assessment of the quality of the target approximation characterized by the model, the assessment of the classification model is utilized. Depending on the model's intended application, diverse performance measures can be used. Since the model is generated based on a training data set, it is crucial for model's quality to check generalization ability. Hence, it important to distinguish between the value of a specific dataset, value of training set and its anticipated performance on the whole domain (Cichosz 2014).

In order to obtain the dataset performance of a model, the value of one or more selected performance metrics on a specific dataset with true class labels existing is calculated. Dataset performance represents the matching degree of the model and the target concept on this dataset. Training performance of the model is determined by the evaluation of the model on the training set that was employed to build the model. While this performance is beneficial for better understanding of the model, it is not of significant interest as the classification of the training data is not the purpose of classification models. Expected performance of the model, on the whole domain, represents its true performance. True performance of the model shows its ability to classify new examples from the given domain correctly. In order to assess the true performance, i.e., to consistently evaluate the unknown values of the accepted performance metrics on the whole domain, comprising generally previously unseen examples, appropriate assessment measures are needed (Cichosz 2014).

k-fold cross-validation is a sophisticated assessment process which handles the tradeoff of bias vs. variance. It randomly divides the existing dataset into k subsets of the same size and then iterates over these subsets. When all k iterations are accomplished, the model built without specific instance in the training set is employed to produce a predicted class label for every instance in the dataset. The resultant vector of predictions is compared to the true class labels utilizing one or more chosen performance measures. The k-fold cross-validation process successfully virtualizes the training and validation or test sets. All existing instances from the set are employed for both model creation and evaluation, but not at the same time (Cichosz 2014).

18.4.1 Performance Measures

Performance measures of model are created by comparing the true class labels of the instances from dataset and the predictions produced by the classifier on the same dataset. For binary classification, a confusion matrix can be characterized with TP as true positive, TN as true negative, FN as false negative, and FP as false positive counts. A new learning problem presented focusses on its domain but ignores a comprehensive analysis. This brings the most employed measure, accuracy, unable to differentiate between the number of correct labels of different classes (Sokolova et al. 2006):

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

In some applications, the number of instances in one class is frequently considerably lower than the overall number of instances. The experimental setting is represented as follows: there is a class of special interest (usually positive) within the set of classes. The rest of the classes are either left, as is in the case of multiclass classification, or combined into one, as in binary classification. The measures of selection are taken for the positive class (Sokolova et al. 2006). The ratio between true positives and false positives is represented by precision.

$$Precision = \frac{TP}{TP + FP}$$

A relation between correctly classified instances and misclassified instances is called recall.

$$Recall = \frac{TP}{TP + FN}$$

$$F - Measure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The F-measure is the harmonic mean of the precision and recall indicators. Recall is a function of its true positives and its false negatives. Precision is a function of true positives and false positives (Sokolova et al. 2006).

Receiver operating characteristic (ROC) employs Cartesian coordinate system in which its y-axis characterizes the true-positive rate, while the x-axis characterizes the false-positive rate. Single point on the ROC plane which visualizes the underlying tradeoff between true positives and false positives characterizes the performance of the classifier. Performance of a classifier which is based only on its scoring function element can be graphically designated utilizing ROC curve. It is essential to determine all possible operating points of a scoring classifier to generate the ROC curve. Occasionally a simple assessment measure is desired even in such more complex cases. Such usually employed measure is the area under the ROC curve (AUC).

During the comparison of models, the model which has greater AUC value is considered superior with respect to its overall predictive performance potential (Cichosz 2014).

Kappa statistic is another performance measure which takes expected figure into account by taking it from the predictor's successes. It represents the result as a proportion of the total for a perfect predictor. The measurement of the consensus between observed and predicted categories of a dataset, and correcting the agreement which happens by chance is achieved by the Kappa statistic (Hall et al. 2011).

18.4.2 ECG Signals Analysis in Diagnosis of Heart Arrhythmia

Cardiovascular disorders (CVDs) are one of the main mortality reasons in worldwide. The creation of accurate and fast techniques for automated ECG heartbeat signal classification is vital for clinical diagnosis of different CVDs (Thaler 2017), e.g., an arrhythmia. Notion arrhythmia is employed to represent a group of circumstances in which irregular electrical activities coming from heart and are characterized by the ECG beats or patterns (Pan and Tompkins 1985; De Chazal et al. 2004). ECG is an effective, simple, noninvasive tool for heart disease recognition. Medical doctors investigate several waveforms based on their characteristics (amplitude, polarity, etc.) and diagnose and treat based on this investigation (Subasi 2019).

Human heart is the most crucial muscle in human body, which together with blood vessels forms cardiovascular system and pumps the blood into each cell of the body. There is no precise heart failure diagnosis tool for detecting the heart failure. The electrocardiogram (ECG) is a noninvasive instrument that acquires electrical activity of the heart and demonstrates the heartbeat irregularities. It shows the possible arrhythmias of the heart or the heartbeat irregularities (Passanisi 2004). Therefore, ECG is an imperative tool for defining the healthiness and the function of the cardiovascular system. Furthermore, it is substantial to describe precise and appropriate diagnosis of physicians to circumvent more damage and to define appropriate approaches and techniques (Son et al. 2012). Still, the problem arises when there is inadequate number of doctors to encounter the requests of patients. Hence, it is essential to implement an ECG based efficient and automated diagnostic systems, together with the machine learning techniques to classify heart beats. These diagnostic schemes support physicians in distinguishing the cardiovascular anomalies (Masetic and Subasi 2016; Subasi 2019).

Different types of arrhythmias exist and each of them is related to a pattern to classify and identify its type. The arrhythmias can be classified into two main groups. The first group composed of arrhythmias formed by a single irregular heartbeat and the other group composed of arrhythmias formed by a set of irregular heartbeats. The classification and identification of arrhythmias can be very difficult since it needs the analysis of each heartbeat of the ECG records, recorded by a Holter monitor, during hours, or even days. Furthermore, physicians can make a mistake during the ECG analysis, due to exhaustion. The employment of computational methods for automated classification of heartbeats is an alternative. Fully automated framework for arrhythmia detection from the ECG can be divided in three stages: (1) ECG signal preprocessing; (2) feature extraction/dimension reduction; and (3) detection/classification (Luz et al. 2016).

MIT-BIH arrhythmia database records taken from the Beth Israel Hospital Arrhythmia Laboratory[1] is used. This database includes 48 two-lead ECG records recorded from 47 different patients, and duration of each of these records is about 30 minutes. Sampling frequency is 360 Hz. Five different heartbeat categories are selected for this study: normal (N), left bundle branch blocks (LBBB), right bundle branch blocks (RBBB), atrial premature contractions (APC), and premature ventricular contractions (PVC) heartbeats (Alickovic and Subasi 2016). The results of classification are shown in Table 18.1.

Table 18.1 presents values for four different evaluation criteria employed in heart arrhythmia classification for nine machine learning techniques. Features have been extracted using discrete wavelet transform from raw ECG signals. The least effective method was LAD Tree with average accuracy of only 87.7%. The best result was achieved with k-NN classifier reaching total accuracy of 98.1%. SVM and ANN also achieved good accuracy. Random forest is the best for F-measure and AUC and k-NN is the best for Kappa statistics.

18.4.3 EEG Signal Analysis in Epileptic Seizure Detection and Prediction

Electroencephalographic (EEG) signals are generally examined by spectrum analysis methods, separating the EEG signal into different frequency bands (α, β, θ, δ). Straightforward spectrum analysis techniques are beneficial when these events are slowly unfolding. But, once transient events such as epileptic seizures happen, bursting series of events or sharp spikes in the recorded signal is seen. The discrete wavelet transform can be used to detect the beginning of the seizure burst. Moreover, it can be used for the onset seizure detection and the termination of seizures (Thakor et al. 2000).

Machine learning techniques are employed to solve biomedical engineering problems and, especially, in biomedical signals analysis. They can accomplish to identify and diagnose in real time. EEG analysis has improved considerably with the extensive use of mathematical modelling and machine learning tools. Machine learning tools have also enabled the classification of patterns within the EEG to enhance the recognition, making EEG signals valuable for recognition of brain disorders and primary pathologies. Therefore, several studies on characteristics of the EEG signals related to neurological diseases have been carried out (Begg et al. 2008).

[1] http://physionet.ph.biu.ac.il/physiobank/database/html/mitdbdir/mitdbdir.htm

Table 18.1 Classification of different ECG heartbeat signals

	Normal	APC	PVC	RBBB	LBBB	Average	F-measure	AUC	Kappa
SVM	0.993	0.947	0.93	0.94	0.997	0.961	0.961	0.976	0.9517
k-NN	1	0.963	0.963	0.983	0.997	0.981	0.981	0.997	0.9767
ANN	1	0.953	0.963	0.977	0.98	0.975	0.975	0.999	0.9683
Random forest	0.953	0.893	0.863	0.883	0.893	0.897	0.998	1	0.9683
CART	0.947	0.85	0.863	0.867	0.92	0.889	0.951	0.973	0.8617
C4.5	0.96	0.907	0.847	0.887	0.917	0.903	0.97	0.982	0.8792
REP tree	0.933	0.833	0.847	0.87	0.92	0.881	0.881	0.953	0.8508
Random tree	0.94	0.883	0.877	0.81	0.91	0.884	0.884	0.928	0.855
LAD tree	0.947	0.827	0.83	0.87	0.91	0.877	0.877	0.981	0.8458

There are around 2 million epilepsy patients in the United States alone, responsive therapeutic intervention facilitated by seizure detection algorithm which increases the efficiency of the method. Raghunathan et al. (2011) devised a two-stage cascaded seizure detection solution, with full detection efficiency. The proposed solution is based on the usage of features that results in unique patterns during the seizure. The proposed technique shows high sensitivity rate and low detection duration. Yuan et al. (2012) proposed a new method for multichannel long-term EEG. Novel nonlinear features of EEG signals are derived from the fractal geometry, as the linear feature comes from the relative fluctuation index. The vector of the feature is then merged into an extreme learning machine for classification. For more stable results, post processing techniques are employed such as smoothing and channel fusion and they are tested on 21 subjects with the segment-based and event-based analysis.

Epilepsy is a severe disease characterized by temporary changes in the bioelectrical functioning of the brain. These fluctuations cause irregular neuronal synchronization and seizures that affect awareness, sensation or movement. Epileptic seizures represent unexpected bursts of wild electrical activity in a group of neurons of the cerebral cortex. Due to the location of the focus (origin) of the electrical activity and sequential enrolment of various brain regions, epileptic seizures may be manifested in numerous ways. For instance, some sort of auditive or visual sensation follows seizures which focus is located in the sensory regions of the cortex. A group of neurons with reduced functionality is referred to as the epileptic focus (Sörnmo and Laguna 2005). Seizure EEG signals contain characteristic patterns that health professionals use to distinguish them from normal (nonseizure) EEG signals. Therefore, their detection may be used to respond to a forthcoming or ongoing seizure. Also, automated recognition techniques have been tested to decrease the amount of data and enable quicker and more accurate detection of pathological EEG waveforms which characterize epileptic seizures. In addition, a few techniques have been suggested to identify spikes in the EEG to predict epileptic events (Begg et al. 2008).

During normal conditions, there is a stable relationship between inhibitory and excitatory signals. The former signals prevent neurons from firing and thus decrease the brain's electrical activity, while the latter signals force neurons to fire. Nonetheless, an important cause of epilepsy lies in impaired balance between these two actions. The reason for producing this imbalance or unstable condition hides inside the neurotransmitters which are responsible for chemical transfer of the signals in the synapse. Consequently, bursts of wild electrical activity will arise when the inhibitory neurotransmitters are being inactive, or the excitatory ones are being excessively active. This neurotransmitter imbalance can be improved by increasing the inhibitory activity or decreasing the excitatory activity, which is the main challenge of antiepileptic drugs (Sörnmo and Laguna 2005).

Epileptic seizures, hardly causing long-lasting injuries or death, may result in loss of consciousness or cause slight mental confusion only. Seizures possess an extremely variable time duration and rate of occurrence. Their duration may range from several seconds to several minutes. There are epileptic patients who experience just a few seizures during the entire life, while some of them have several seizures during a single day. Therefore, (Niedermayer 1999) built a scheme to classify seizures into groups based on the EEG characteristics. Groups are formed based on the epileptic seizure focus (origin): primary generalized seizures include the whole brain, while partial seizures start in a limited brain area. The latter group is associated with a single epileptic focus, which cannot be said for the former group. Therefore, some partial seizures by eliminating a small part of the cortex during surgery can be treated. To make sure that the location of the epileptic focus is correctly bordered, a series of very systematic and in-depth studies and examinations must be carried out before the surgery. A partial seizure may sometimes progress to other brain areas. Such seizure is denoted as a partial seizure with secondary generalization (Sörnmo and Laguna 2005).

Health specialists use distinctive patterns within ictal (seizure) EEG waveforms to differentiate them from interictal (nonseizure) EEG waveforms. Any form of long-term EEG monitoring creates huge amounts of data as a result. This data requires a lot of time to be properly analyzed. In order to reduce the amount of data and allow quicker and better detection of abnormal EEG signals related to epileptic seizures, automatic detection systems have been tested. Moreover, a few methods have been suggested to predict epileptic seizures by discovering spikes in the EEG. Several signal processing techniques considering mathematical representation of interictal and ictal data are essential for the design of these detection algorithms (Y. Khan and Gotman 2003). Noise and artifact elimination are an additional factor that should be taken into consideration. An effective seizure prediction algorithm may warn a patient wearing an ambulatory recording device to consider proper security actions before the seizure occurs (Sörnmo and Laguna 2005).

A medical application designed to control seizures comprises of two systems (Winterhalder et al. 2003): (1) a seizure prediction algorithm raising an alarm when it senses an upcoming seizure and (2) a system acting to control a seizure. Moreover, one simple alert of upcoming seizure may be enough for a patient to leave dangerous situations or actions, like climbing stairs or playing sports. Seizure prediction methods are based on the extraction of EEG features, calculated over a short time window of a few seconds to a few minutes. There exist univariate measures, calculated separately for each EEG channel, and bivariate (or multivariate) measures, which quantify some relationship between two or more EEG channels (Subasi 2019).

Table 18.2 presents values for four different evaluation criteria employed in epileptic seizure detection and prediction for nine machine learning techniques. Features have been extracted using discrete wavelet transform from raw ECG signals. The least effective method was Random Tree with average accuracy of only 94.3%. The best result was achieved with SVM classifier reaching total accuracy of 98.7%. Random forest is the second best among the classifiers with a total accuracy of 98.5%. F-measure of the classifiers is almost the same as total accuracy results. Random forest is the best for AUC and Kappa statistics with a value of 0.999.

Table 18.2 Classification of different EEG signals for epileptic seizure prediction and detection

	Interictal	Preictal	Ictal	Average	F-measure	AUC	Kappa
SVM	0.997	0.973	0.99	0.987	0.987	0.992	0.98
k-NN	0.987	0.918	0.967	0.957	0.957	0.968	0.936
ANN	0.981	0.95	0.955	0.962	0.962	0.987	0.943
Random forest	0.997	0.969	0.988	0.985	0.985	0.999	0.999
CART	0.977	0.936	0.942	0.952	0.952	0.965	0.9275
C4.5	0.978	0.946	0.961	0.962	0.962	0.974	0.9425
REP tree	0.977	0.937	0.953	0.956	0.956	0.986	0.9335
Random tree	0.962	0.922	0.945	0.943	0.943	0.957	0.9145
LAD tree	0.973	0.91	0.958	0.947	0.947	0.992	0.9205

Table 18.3 Classification of different EMG signals for diagnosis of neuromuscular disorders

	Control	Myopathy	ALS	Average	F-measure	AUC	Kappa
SVM	0.989	0.986	0.999	0.991	0.991	0.995	0.9871
k-NN	0.972	0.976	0.997	0.981	0.981	0.986	0.9721
ANN	0.98	0.975	0.998	0.984	0.984	0.998	0.9767
Random forest	0.974	0.984	0.999	0.986	0.986	1	0.9788
CART	0.933	0.949	0.993	0.958	0.958	0.976	0.9375
C4.5	0.947	0.952	0.989	0.963	0.962	0.975	0.9437
REP tree	0.937	0.953	0.985	0.958	0.958	0.985	0.9375
Random tree	0.913	0.928	0.968	0.936	0.936	0.952	0.9042
LAD tree	0.941	0.955	0.985	0.96	0.96	0.993	0.9404

18.4.4 EMG Signal Analysis in Diagnosis of Neuromuscular Disorders

The needle EMG is the usual clinical recording method employed for diagnosis of the neuromuscular pathology. Once a patient goes to a doctor for muscle weakness, recording of the needle EMG during contraction of specific muscles will be done. The morphology of single MUAP waveforms gives necessary clinical data regarding the muscle's skill to answer to the central nervous system. This data may assist to identify irregular activity happening in situations like muscles irritation, injury to nerves in the arms and legs, pinched nerves, and muscular dystrophy. The needle EMG is also investigated together with nerve wound and can be employed to find out if the wound restores and go back to normal with complete muscle re-activity, for instance, by analyzing alterations in motor unit accomplishment over a definite time period. The diagnostic EMG comprises of investigation of unplanned motor action that can be throughout muscle relaxation. In ordinary situations, the muscle is electrically quiet during relaxation period; on the other hand, irregular unplanned waveforms and waveform patterns can be produced that are connected with spontaneous muscular activities and seizures (Sörnmo and Laguna 2005; Subasi 2019).

Table 18.3 presents values for four different evaluation criteria employed in diagnosis of neuromuscular disorders for nine machine learning techniques. Features have been extracted using discrete wavelet transform from raw ECG signals. The least effective method was Random Tree with average accuracy of only 93.6%. The best result was achieved with SVM classifier reaching total accuracy of 99.1% and F-measure of 0.991. Random forest is the second best among the classifiers with a total accuracy of 98.6%. F-measure of the classifiers is almost the same as total accuracy results. Random forest is the best for AUC with a value of 1. SVM is the best for the Kappa statistics with a value of 0.9871.

18.5 Discussion and Conclusions

Biomedical signals are principally used to diagnose or detect specific pathological or physiological conditions. Additionally, these signals are employed to analyze biological systems in the healthcare. Biomedical signals are utilized in the research laboratory, clinic, and even at home. The ECG, the EEG, and the EMG are the widely used examples of the biomedical signals. In healthcare, biomedical signals are utilized to detect physiological or pathological conditions and diagnose different disorders. Biomedical signal analysis is utilized to remove the noise, create accurate signal model and analyze its components, and predict pathological events in the brain, heart or muscle (Muthuswamy 2004). Biomedical signals include information to recognize the complex pathophysiologic mechanisms. However, such information may not be attainable directly from the raw signals suppressed in additive noise. Because of these reasons, biomedical signal processing is needed to enhance the related information and to designate the level of pathology for routine clinical diagnosis, rehabilitation or therapy. Several signal processing techniques can be used for denoising, filtering, spectral estimation, and feature extraction (Mainardi et al. 2006).

Time-frequency feature extraction techniques are used for the analysis and interpretation of biomedical signals with time-varying characteristics. For instance, the P-QRS-T characteristic of the ECG signals show localized low frequencies in the P- and the ST-segments and high frequencies in the QRS complex. The QRS segment can be localized by means of time-frequency analysis such as discrete wavelet transform. Moreover, neurological signals with potential applications in the analysis of EEG, and epileptic spikes and seizures can be analyzed by discrete wavelet transform. The need for an effective analysis of biomedical signals with time-frequency methods is apparent, and spectral variations can be well localized with them. Analyzing the signal at different scales can achieve meaningful information. The discrete wavelet transform seems to have strong theoretical features permitting innovative interpretation of biomedical signals (Thakor et al. 2000).

Machine learning algorithms offer a powerful tool for the biomedical signal analysis. This chapter has reviewed the biomedical signals such as ECG, EEG, and EMG and applications of machine learning methods in cardiology, neurology, and brain signals. Machine learning methods have been employed broadly in different fields including biomedical signal analysis. In addition to these applications, many studies is still going on to find optimal values for the parameters and optimal algorithms employed in these techniques (Micheli-Tzanakou 2000).

Three different biomedical signals, namely, ECG, EEG, and EMG signal analysis, and classification results are presented in this chapter as an example of biomedical signal usage in healthcare. For each type of biomedical signal dataset, the analysis results are given in Tables 18.1, 18.2, and 18.3. The SVM, ANN, k-NN, and random forest classifiers achieved better results in most of the cases.

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