Chapter 1
Introduction to EMG Technique and Feature Extraction

The electromyography (EMG) signal is electrical indication of the neuromuscular actuation connected with a contracting muscle. It is an exceedingly complicated sign which is influenced by the anatomical and physiological properties of muscles, the control plan of the fringe sensory system, and also the attributes of the instrumentation that is utilized to identify and watch it. Most of the connections between the EMG signal and the properties of a contracting muscle which will be quickly utilized have developed serendipitously. The absence of a fitting portrayal of the EMG signal is likely the most noteworthy single variable which has hampered the improvement of EMG into an exact discipline.

This section will show two fundamental ideas. The first is a discourse of an organized approach for deciphering the data content of the EMG signal. The scientific model which is created is built with respect to current learning of the properties of contracting human muscles. The degree to which the model helps to the understanding of the sign is confined to the constrained sum of physiological learning right now accessible. On the other hand, even in its available structure, the demonstrating methodology supplies an edifying knowledge into the arrangement of the EMG signal.

EMG is the investigation of muscle capacity through examination of the electrical signs radiated amid brawny constrictions. EMG is frequently misused and abused by numerous clinicians and scientists. Ordinarily even accomplished electromyographers neglect to give enough data and detail on the conventions, recording supplies and techniques used to permit different analysts to reliably recreate their studies. Assuredly, this part will elucidate some of these issues and give the peruser a premise for having the capacity to direct EMG examines as a feature of their on-going exploration.

EMG is measuring the electrical sign connected with the enactment of the muscle. This may be willful or automatic muscle compression. The EMG action of willful muscle withdrawals is identified with pressure. The practical unit of the muscle compression is an engine unit, which is embodied a solitary alpha

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engine neuron and all the strands it exhausts. This muscle fiber contracts when the activity possibilities (drive) of the engine nerve which supplies it achieves a depolarization limit. The depolarization creates an electromagnetic field and the potential is measured as a voltage. The depolarization, which spreads along the film of the muscle, is a muscle activity potential. The engine unit activity potential is the spatio and transient summation of the individual muscle activity possibilities for all the filaments of a solitary engine unit. In this way, the EMG sign is the arithmetical summation of the engine unit activity possibilities inside the pick-up territory of the terminal being utilized. The pick-up zone of a cathode will quite often incorporate more than one engine unit on the grounds that muscle filaments of distinctive engine units are mixed all through the whole muscle. Any bit of the muscle may contain filaments having a place with upwards of 20–50 engine units.

A solitary engine unit can have 3–2,000 muscle filaments. Muscles controlling fine developments have more modest quantities of muscle filaments for every engine units (typically short of what 10 strands for every engine unit) than muscles controlling extensive terrible developments (100–1,000 strands for every engine unit). There is a chain of importance game plan amid a muscle compression as engine units with less muscle strands are normally enlisted initially, taken after by the engine units with bigger muscle filaments. The quantity of engine units for every muscle is variable all through the body.

With the end goal of this part there are two fundamental sorts of EMG: clinical (frequently called indicative EMG) and kinesiological. Symptomatic EMG, normally done by physiatrists and neurologists, are investigations of the characteristics of the engine unit activity potential for span and abundancy. These are commonly done to help analytic neuromuscular pathology. They likewise assess the spontaneous releases of loose muscles and have the capacity confine single engine unit action. Kinesiological EMG is the sort most found in the writing in regards to development dissection. This kind of EMG studies the relationship of bulky capacity to development of the body fragments and assesses timing of muscle action with respect to the developments. Moreover, numerous studies endeavor to look at the quality and energy generation of the muscles themselves.

There is a relationship of EMG to numerous biomechanical variables. Regarding isometric withdrawals, there is a positive relationship in the increment of pressure inside the muscle as to the plentifulness of the EMG sign recorded. There is a slack time, on the other hand, as the EMG adequacy does not specifically match the manufacture up of isometric pressure. One must be watchful when attempting to gauge energy creation from the EMG signal, as there is sketchy legitimacy of the relationship of power to plentifulness when numerous muscles are intersection the same joint, or when muscles cross different joints. At the point when taking a gander at muscle movement, as to concentric and unconventional compressions, one finds that flighty withdrawals create less muscle action than concentric withdrawal when conflicting with equivalent energy. As the muscle exhausts, one sees a diminished strain regardless of steady or considerably bigger adequacy of the muscle action. There is a loss of the high-recurrence segment of the sign as one uniform, which can be seen by a diminishing in the average recurrence of the muscle signal. Amid movement, there has a tendency to be an association with EMG and speed of the development. There is an opposite relationship of quality creation with concentric withdrawals and the velocity of development, while there is a positive relationship of quality generation with unconventional constrictions and the pace of development. One can deal with even more a heap with unconventional contractions at higher rate. For instance: If a weight was huge and you brought it down to the ground in a quick, yet controlled way, you took care of a vast weight at a rapid through flighty compressions. You would not have the capacity to raise the weight (concentric withdrawal) at the pace you had the capacity lower it. The constrained generation by the strands are not so much any more noteworthy, yet you had the capacity handle a bigger measure of weight and the EMG action of the muscles taking care of that weight would be littler. In this manner, we have a reverse relationship for concentric withdrawals and positive relationship for offbeat constrictions regarding pace of development.

As to recording the EMG signal, the adequacy of the engine unit activity potential relies on upon numerous elements which include: breadth of the muscle fiber, separate between dynamic muscle fiber and the location site (fat tissue thickness), and sifting properties of the terminals themselves. The target is to get a sign free of noise (ie., development relic, 60 Hz ancient rarity, and so on). Along these lines, the anode sort and enhancer qualities assume a vital part in getting a commotion free flag.

Development and position of appendages are controlled by electrical signs going here and there and then here again between the muscles and the fringe and focal sensory system. At the point when pathologic conditions emerge in the engine framework, whether in the spinal rope, the engine neurons, the muscle, or the neuromuscular intersections, the attributes of the electrical flag in the muscle change. Watchful enlistment and investigation of electrical flag in muscle (electromyograms) can along these lines be an important support in finding and diagnosing abnormalities in the muscles as well as in the engine framework overall. EMG is the enlistment and elucidation of these muscle activity possibilities. As of not long ago, electromyograms were recorded fundamentally for exploratory or analytic purposes; be that as it may, with the headway of bioelectric innovation, electromyograms likewise have turned into an essential device in accomplishing manufactured control of appendage development, i.e., practical electrical incitement (FES) and restoration. This part will concentrate on the symptomatic application of electromyograms. Since the ascent of advanced clinical EMG, the specialized strategies utilized as a part of recording and dissecting electromyograms have been managed by the accessible innovation. The concentric needle cathode introduced by Adrian and Bronk in 1929 gave a simple-to-utilize anode with high mechanical qualities and steady, reproducible estimations. Supplanting of galvanometers with high-pickup speakers permitted more modest terminals with higher impedances to be utilized and possibilities of littler amplitudes to be recorded. With these specialized accomplishments, clinical EMG soon advanced into a very particular field where electromyographists with numerous years of experience read and deciphered long paper EMG records focused around the visual appearance of the electromyograms. Gradually, a more quantitative methodology developed, where peculiarities, for example, potential term, crest-to-top adequacy, and number of stages, were measured on the paper records and contrasted, and a set of ordinary information accumulated from solid subjects of all ages. In the most recent decade, the universally useful rack-mounted supplies of the past have been supplanted by thus nomically planned EMG units with incorporated machines. Electromyograms are digitized, transformed, put away on removable media, and shown on machine screens with screen designs that change in agreement with the sort of recording and dissection picked by the examiner.

In light of this, this section gives an acquaintance with the essential ideas of clinical EMG, a survey of fundamental life structures, the source of the electromyogram, and a percentage of the primary recording strategies and sign investigation methods being used.

1.1 Structure

Muscles represent around 40 % of the human mass, running from the little extraocular muscles that turn the eyeball in its attachment to the expansive appendage muscles that create motion and control carriage. The configuration of muscles differs relying upon the scope of movement and the energy pushed. In the most straightforward game plan (fusiform), parallel filaments expand the full length of the muscle and connect to tendons at both closures. Muscles creating an extensive power have a more entangled structure in which a lot of people short muscle filaments join to a level tendon that stretches out over an expansive part of the muscle. This mastermind ment (unipennate) expands the cross-sectional territory and along these lines the contractile energy of the muscle. At the point when muscle filaments fan out from both sides of the tendon, the muscle structure is alluded to as bipennate.

A lipid bilayer (sarcolemma) encases the muscle fiber and differentiates the intracellular myoplasma from the interstitial liquid. Between neighboring filaments runs a layer of connective tissue, the endomysium, made principally out of collagen and elastin. Packs of filaments, fascicles, are held together by a thicker layer of connective-tissue called the perimysium. The entire muscle is wrapped in a layer of connective tissue called the epimysium. The connective tissue is constant with the tendons appending the muscle to the skeleton.

In the myoplasma, meager and thick fibers interdigitate and structure short, serially associated indistinguishable units called sarcomeres. Various sarcomeres associate end to end, accordingly framing longitudinal strands of myofibrils that augment the whole length of the muscle fiber. The aggregate shortening of a muscle amid constriction is the net impact of all sarcomeres shortening in arrangement all the while. The individual sarcomeres abbreviate by structuring cross-connects between the thick and dainty fibers. The cross-scaffolds pull the fibers to one another, along these lines expanding the measure of longitudinal cover between the thick and slight fibers. The thick grid of myofibrils is held set up by a structural system of between intercede fibers made out of desmin, vimetin, and synemin (squire, 1986).

At the site of the neuromuscular intersection, each one engine neuron structures insurance grows and innervates a few muscle strands circulated practically equally inside a curved or roundabout district extending from 2 to 10 mm in width. The engine neuron and the muscle strands it innervates constitute a useful unit, the engine unit. The cross-area of muscle involved by an engine unit is known as the engine unit domain (MUT). A regular muscle fiber is just innervated at a solitary point, found inside a cross-sectional band alluded to as the end-plate zone. While the width of the end-plate zone is just a couple of millimeters, the zone itself may stretch out over a huge piece of the muscle. The quantity of muscle strands for every engine neuron (i.e., the innervation degree) ranges from 3:1 in extraneous eye muscles where fine-evaluated withdrawal is obliged to 120:1 in some appendage muscles with coarse development (kimura, 1981). The filaments of one engine unit are intermixed with strands of other engine units; hence, a few engine units dwell inside a given cross-area. The filaments of the same.

EMG is technique to evaluate and record the electrical activity of the muscle and is a valuable device to assess neuromuscular disorders. Computer-aided EMG has evolved as an indispensable tool in the everyday activity of neurophysiology laboratories in facilitating quantitative analysis and decision making in the clinical neurophysiology, rehabilitation, sport medicine and human physiology. EMG findings are used to detect and describe special disease processes affecting the Motor Unit (MU), which is the smallest functional unit of the muscle [1] (Fig. 1.1).

In EMG-based model recognition, sEMG signal is pre-processed from the spectral frequency component of the signal and is extracted with some features before performing classification [2] (Fig. 1.2).

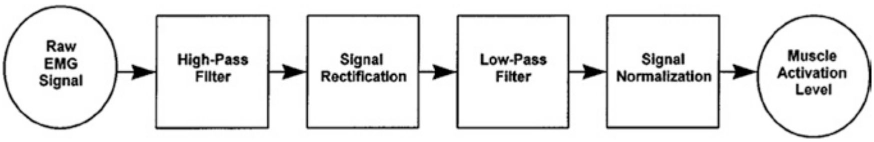


Fig. 1.1 Electromyogram signal processing algorithms to estimate the level of muscle activity

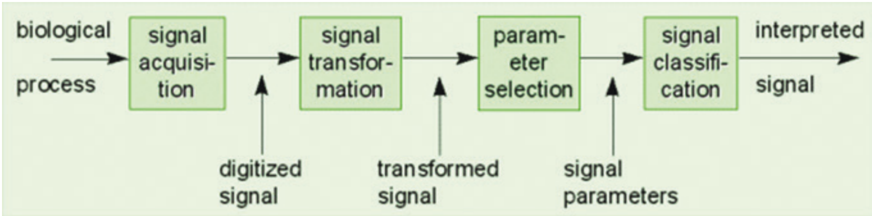


Fig. 1.2 Signal processing

Normally, in pre-processing and signal condition process, procedure to remove noise is a significant step to reduce noises and improve some spectral component part [3]. Next important step, feature extraction, is used for highlighting the relevant structures in the sEMG signal and rejecting the noise and unimportant sEMG signal [4]. The success of EMG pattern recognition depends on the selection of features that represent raw sEMG signal for its classification. This study is enforced by the fact that the limitation of the solution to remove WGN in the pre-processing step and EMG-based gestures classification need to conduct the extraction step. The selection of the feature that tolerance of WGN and modification of existing EMG feature to improve the robust property are proposed. Resultantly, WGN removal algorithms in the preprocessing step are not needed.

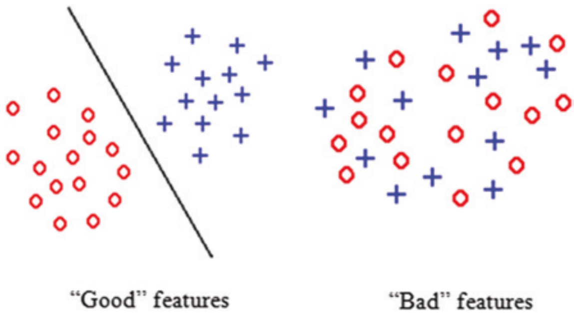
Feature extraction is a method to extract the useful information that is hidden in surface EMG signal and to remove the unwanted EMG parts and interferences [4, 5] (Fig. 1.3).

Some features are strong across different kinds of noises; consequently, intensive data pre-processing methods shall be avoided to be implemented [6]. In addition, appropriate features approaches high classification accuracy [7]. Three properties have been suggested for use in quantitative comparison of their capabilities that include maximum class separability, robustness, and complexity [4, 5]. Although many research works have mainly tried to explore and examine an appropriate feature vector for numerous specific EMG signal classification applications (e.g. [4–8]), there are other works which made deeply quantitative comparisons of their qualities, particularly in redundancy point of view [9].

Furthermore, most recent EMG signal classification studies have still employed set of feature vectors that carried a number of redundant features (e.g. [10–17]).

In 1975, the Graupe and Cine showed that a fourth-order time-series model of EMG signals can be classified by a linear discrimination function [18], but this technique involves a high complexity in computation. The results of Kelly and Parker's work illustrated that a Hopfield neural network could produce AR coefficients from EMG signals in a shorter time [19]. Furthermore, Saridis and Gootee presented integral absolute value and zero-crossing features that could produce appropriate feature space in turn to classify arm motions [20]. Zardoshti and folks [4] extracted few features such as integral of absolute value, variance,

Fig. 1.3 For feature extraction template+



number of zero crossings and auto-regressive model parameters from upper limb EMG signals and then evaluated them with K-nearest neighbor (a non-parametric classifier). They presented a new feature, EMG histogram, which is highly suitable for the classification of hand motions, and showed that this feature is appropriate to calculate both speed and noise tolerance. Chang and folks [21] used the variance of the rectified wave envelope and IAV features and Mahalonobius distance to classify four pre-shaping grasp movements. They also showed that these features could classify movements up to 90 % accuracy. Kang and folks (1995) compared AR and cepstrum coefficients and showed that the cepstrum coefficients are quite useful to improve classification rate. The time frequency transform has also been introduced as a new mathematical approach to time–frequency domain. Biomedical signals, especially EMG signals, have been processed by time–frequency transforms in order to extract more representative features to improve rate of classification of motions. In this way, Jung and folks [22] imposed Wigner–Ville transform on upper limb EMG signals to classify six different movements. Wellig and Moschytz [23] too used packet wavelet transform to decompose EMG signals and reduce misclassification rate. Liyu et al. [24] distinguished four forearm motions by decomposing two channels of EMG signals with wavelet transform in six levels, and finally classified these coefficients by an artificial neural network (ANN) classifier. Abel and folks [25] by applying inter-scale local maximum method on wavelet coefficients of EMG signals presented new features, which improved classification rate among neuropathic, myopathic and normal groups. Englehart et al. [26] extracted upper limb EMG signals from four channels and then, by extracting wavelet coefficients, reduced their dimensions by PCA transform, and finally misclassification rate was decreased. Although literature includes many papers which explore extraction of features from EMG for controlling prosthetic limbs, there have been few works which make quantitative comparison of their quality. Christodoulos and Pattichis [27] used an ANN based on unsupervised learning and a statistical pattern recognition technique based on Euclidean distance to analyze a total of 1213 MUAP's obtained from 12 normal subjects, 13 subjects suffering from myopathy, and 15 subjects suffering from motor neuron disease and they reported success rate for used ANN technique as 97.6 % and for statistical technique 95.3 %. In 2005, Huang et al. [41] used Gaussian Mixture Model on a 12 subject database to classify subjects according to feature sets including time-domain (TD) features and autoregressive features with root mean square value (AR + RMS). They reported Gaussian mixture model (GMM) achieves 96.91 % classification accuracy using a AR + RMS + TD feature set and attains 96.3 % classification accuracy using a AR + RMS feature set for distinguishing six limb motions. Tsenov et al. [28] in 2006 exploited signal recorded at surface of skin of forearm to provide recognition of movement of hand and finger movements of healthy subjects. They utilized radial basis function (RBF), multilayer perceptron (MLP) and LVQ networks to classify signals based on time domain extracted features as Mean Absolute Value, Variance, Waveform Length, Norm, Number of Zero Crossings, Absolute Maximum, Absolute Minimum, Maximum minus Minimum and Median Value. They reported average classification rates of 92.64 % (10 neurons in hidden layer as best case), 83.82 % (spread value 0.7) and 88.23 % (28 competitive neurons as best case) for MLP, RBF and LVQ networks, respectively.

In 2007, Yoshikawa et al. [29] extracted features MAV, VAR, WL, ZC, Absolute Maximum, Absolute Minimum and Median Value for motion classification based on SVM. In same year, Momen et al. [30] presented a real-time EMG classifier of user-selected intentional movements for signals recorded from forearm extensor and flexor muscles of seven able bodies-subjects and one congenital amputee. Segmentation of feature space was performed using fuzzy C-means clustering. It was reported that with only 2 min of training data from each user classifier discriminated four different movements with an average accuracy of 92.7 % $\pm$ 3.2 %. It was stated in their work that presented method may facilitate development of dynamic upper extremity prosthesis control strategies using arbitrary, user-preferred muscle contractions (Fig. 1.4).

Hudgins et al. [31] were pioneers in developing a real-time pattern-recognition-based MCS. Using TD features and a MLP neural network, they succeeded in classifying four types of upper limb motion, with an accuracy of approximately 90 %. This work was continued over last 15 years, by employing various classifiers, such as linear discriminant analysis (LDA) [32, 33], MLP/RBF neural networks [34], time-delayed ANN [35], fuzzy [36, 37], Neuro-Fuzzy [38], fuzzy ARTMAP networks [39], fuzzy-MINMAX networks [40], GMMs [41–43], and hidden Markov models (HMMs) [44]. Vuskovic and Du [39] introduced a modified version of a fuzzy ARTMAP network to classify prehensile MESs. Englehart et al. [32] showed that LDA, outperforms MLP on time-scale features that are dimensionally reduced by PCA. In addition, significant results were achieved using probabilistic approaches. Chan and Englehart [44] applied an HMM to discriminate six classes of limb movement based on a four-channel MES. It resulted in an average accuracy of 94.63 %, which exceeded an MLP-based classifier used in [33] (93.27 %). Furthermore, Huang et al. [41] and Fukuda et al. [42] developed a GMM as a classifier in their MCS; former showed an accuracy of approximately 97 %. Englehart et al. [33] introduced a continuous classification scheme that provided more robust results for a shortened segment length of signal, and high-speed controllers. Oskoei and Hu [7] employed SVM for classification of upper limb motions suing myoelectric signals. They used another method to adjust SVM parameters before classification, and examined overlapped segmentation and majority voting to improve controller performance. They also used a TD multi-feature set (i.e., MAV + WL + ZC + SSC) as signal features for classification.

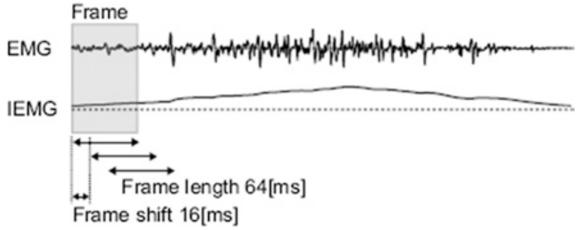


Fig. 1.4 EMG and IEMG signals with feature extraction frame

In this book, we follow a high quality EMG feature space which has following properties:

Maximum class separability. A high quality feature space which results in clusters that have maximum separability or minimum overlap. This ensures lowest possible misclassification rate.

Robustness. Lowest possible sensitivity of feature space cluster separability to noise samples.

Complexity. Lowest possible computational complexity of features (and clusters) so that procedure can be implemented with reasonable hardware and in a real-time manner.