International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:7, No:11, 2013

Review of Surface Electromyogram Signals: Its Analysis and Applications

Anjana Goen, D. C.Tiwari

***Abstract*—**Electromyography (EMG) is the study of muscles function through analysis of electrical activity produced from muscles. This electrical activity which is displayed in the form of signal is the result of neuromuscular activation associated with muscle contraction. The most common techniques of EMG signal recording are by using surface and needle/wire electrode where the latter is usually used for interest in deep muscle. This paper will focus on surface electromyogram (SEMG) signal. During SEMG recording, several problems had to been countered such as noise, motion artifact and signal instability. Thus, various signal processing techniques had been implemented to produce a reliable signal for analysis. SEMG signal finds broad application particularly in biomedical field. It had been analyzed and studied for various interests such as neuromuscular disease, enhancement of muscular function and human-computer interface.

***Keywords*—**Evolvable hardware (EHW), Functional Electrical Simulation (FES), Hidden Markov Model (HMM), Hjorth Time Domain (HTD).

I. Introduction

THIS paper reviews the works on the surface electromyography (SEMG) signal processing and its analysis for engineering research in diverse areas such as rehabilitation, movement analysis, myoelectric control of prosthesis, grasp recognition, human machine interaction, speech recognition, Parkinson disease and clinical applications and diagnosis. The paper begins with the brief description of myoelectric signal generation and next the explanation of various signal processing techniques applied for SEMG signal. The techniques include methods of signal acquisition, noise removal and analysis of signals in time and frequency domain. In the last, this paper looks at several works and literatures on application of SEMG signal in various fields such as control of prosthetic device, nerve conduction velocity, motion analysis, clinical diagnosis and speech recognition. The paper is concluded after compiling several recent works on the usage of SEMG signal processing and analysis. The objective of the paper is to make the researchers acquainted with different techniques available for analysis and interpretation of SEMG signal also different techniques can be employed for a particular purpose.

Anjana Goen is with the department of Electronics and Communication Engineering in Rustamji Institute of Technology, Tekanpur and Research Scholar at Jiwaji University, Gwalior, India (phone: +919425755052, e-mail: anjana_1999@yahoo.co.in).

D. C. Tiwari is, Professor in School of Studies in Electronics at Jiwaji University, Gwalior, India (e-mail:dctiwari_1999@yahoo.co.in).

II. Myoelectric Signal

Electromyography (EMG) is a technique for evaluating and recording the electrical activity called myoelectric signals produced by skeletal muscles. Myoelectric signals are formed by physiological variations in the state of muscle fiber membranes during voluntary, involuntary or stimulated contractions. EMG nowadays has become an important parameter in biomedical and clinical applications. Thus detection, processing, interpretation and analysis of EMG signal had become a major research area in biomedical field involving wide range of expertise from physician, engineer to computer scientist. Study of EMG is said to begin as early as 17th century. With the development of modern electronic devices and equipments along with new techniques in signal processing and mathematical models there is intense study of EMG signal from the last two decades.

The origin of EMG is closely related to the work of nervous system. It is a complicated signal, controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. Electrochemical transmission between nerves starting from the brain produces action potential which propagates through nerve fibers and finally stimulates the skeletal muscle. This stimulation creates muscle contraction which results in movement of human limbs. Action potential acts on a single nerve and there is vast number of skeletal muscle fibers. Thus, the electrical potential from muscle recorded for EMG is actually superposition of action potentials acting on skeletal fiber muscles [1].

EMG signal is representation of electrical potential in the form of time varying signal. By studying EMG, one actually looks into the characteristics of body movement due to muscle contraction activity. Kinesiological EMG is study of the voluntary neuromuscular activation of muscles within postural tasks, functional movements, work conditions and treatment/training regimes. It is established as an evaluation tool for applied research, physiotherapy/ rehabilitation, sports training and interactions of the human body to industrial products and work conditions. Obtaining EMG signals from human includes several processes involving recording, data acquisition, signal conditioning and processing. Recording of EMG signal is done by means of electrodes. Three types of electrodes wire, needle and surface are commonly used where the latter being the most widely used being non-invasive [2]. EMG signal obtained with different types of electrodes may have different characteristics. To specify the type of electrode used for recording the EMG signal is generally termed as ‘Surface EMG’ or ‘Needle EMG’ in almost every literature.

This paper reviews most of the literatures employing 'Surface EMG'.

Surface electromyography (SEMG) provides a non-invasive way of studying muscular function. It is very complex, representing a summation of tissue-filtered signals generated by a number of concurrently active motor units. The generated motor unit action potentials (MUAPs) recorded on the skin surface varies in amplitude, duration and frequency content [1]. SEMG has been used effectively for functional electrical stimulation (FES) or for the controlling of artificial limbs but, its use in clinical diagnosis has been very limited or non-existent [3]. A number of studies have shown that SEMG generated by either voluntary or electrically elicited muscle activity, contain more significant information than it was originally believed [4].

Fig. 1 Gel Electrodes

Fig. 2 Raw surface EMG signal

A. Surface EMG Signal Acquisition and Amplification

Raw Surface EMG is relatively small in amplitude ranging from 0 to 10 mV (peak-to-peak) or 0 to 1.5mV (rms) and frequency range lies between 0 to 500 Hz, but the usable energy is dominant between 50-150 Hz. When the muscle is relaxed, a more or less noise-free EMG baseline can be seen. The raw EMG baseline noise depends on many factors, especially the quality of the EMG amplifier, the environment noise and the quality of the given detection condition. The amplitude of EMG signal is too small for further processing. The signal is amplified using differential amplifiers and it rejects or eliminates artifacts. An instrumentation amplifier is used to amplify the signal but a pre-amplifying stage is necessary to provide initial amplification which converts the signal to a low level of impedance before it is fed to the main amplifier [5]. Instrumentation amplifier could be constructed using general purpose op-amp such as LM 741 or integrated circuit (IC). Instrumentation amplifier IC commonly used in literatures are the Burr-Brown INA 102 [5], Analog Devices AD 620 [6], [7] and Texas Instruments INA 128 [8]. The amplification gain varies from 1000 to 50000 according to the amplifier manufacturer.

B. Noise Removal

An unfiltered unprocessed signal detecting the superposed MUAPs is called a raw EMG Signal. A raw EMG signal sometimes contains inevitable noise. With the presence of noise, the data of muscle contraction characteristic would no longer be genuine. Noise in EMG signal may emanate from various sources i) inherent noise in electronics equipment ii) ambient noise from electromagnetic radiation, iii) motion artifact and iv) inherent instability of the signal [9]. Noise could also originate from the electrode. The metal-electrolyte contact of electrode is intrinsically noisy and has become an important factor in EMG noise. It is also a limiting factor for detection of very small potentials.

An EMG recording system with wire that connects surface electrode with the adjacent amplifying equipment could be vulnerable to pick up main hums and other electrical interference. Therefore, to solve the noise problem which might results from using lengthy wire a pair of surface electrode combined with differential amplifier in a single module was proposed [10]. The preamplifier circuit built for this module has operational characteristics which allow surface EMG signals to be recorded with effective suppression of extraneous electrical interference. This device is called miniature skin-mounted preamplifier had been used in several literatures.

Motion artifact is another source of noise. It could be caused by electrode movement on skin surface and electrode cable. Noise produced by motion artifact is in the range of 0 to 20 Hz and can be filtered out by using high pass filter [11]. Regardless of motion artifact noises, SEMG signal in 0 to 20 Hz range do provide significant information on firing rates of active motor units [12]. However, in most works, information contained in signal of this range is not of interest. There are cases where artifact noise is unavoidable due to natural and intentional causes. For example works on removing motion artifact from surface EMG recordings in Whole Body Vibration [13]. Vibration training is used in sport medicine to enhance athletic performance. Surface EMG recording is one on subject undergoing vibration training for muscle activity evaluation. The vibration would produce motion artifact and creates noise. They used adaptive filtering to abolish such noise. Accelerometers are placed onto platform or directly on muscles providing error signal shape to be cancelled from the raw SEMG signal. The results obtained shows effective cancellations of the vibration frequency.

In general, surface electrode is used to pick up any biosignal. Obviously, interference from other biosignal is very likely during surface EMG recording. Electrocardiography (ECG) is the most common source of interference and often known as ECG artifact. A number of literatures had studied location of surface EMG recording that affected by ECG artifact. Among the muscle location that is vulnerable to ECG interference are trunk muscles [14], [15] back muscles [16], [17] and chest. Various methods had been studied for ECG artifact removal from SEMG signal. High-pass filtering using Butterworth filter is probably the most simple and straightforward idea. Value of cut-off frequency must be chosen in the way that it would not affect the real SEMG signal. The optimal value of cut-off frequency as proposed in some literatures would be around 30 Hz [18]-[19]. However, high-pass filtering is not the only way. Adaptive ECG spike clipping in addition to digital high-pass filter had been also used [20]. In this work, SEMG signal is collected from pectorialis major muscles of adult male subjects. For digital high-pass filter, cutoff frequency varied between 10 to 100 Hz and the order varied from 1 to 6. Adaptive ECG spike clipping on the other hand is a threshold-based suppression method. Signal amplitude that exceeds the threshold value will be clamped to the threshold. Both methods are effective in removing ECG artifact. But when combined, the SNR performance improved by 14% over the two methods individually.

Adaptive filter is another method that had been used for ECG artifact removal [17], [21], [22]. Raw SEMG signal containing ECG artifact is subtracted with a reference signal which is correlated with the ECG signal [17]. The result is a denoised signal which is the estimate of the SEMG signal of interest. Adaptive filtering provides an efficient tool for ECG rejection with advantage of ability to rejects all components correlated to QRS complex [17].

Another source of noise in SEMG signal is the power lines with frequency of 50 or 60 Hz. Digital notch filter, spectrum interpolation [23] and adaptive filtering [24] can be used for noise removal. Notch filter could be designed with notch centered at power lines frequency and 1Hz width. However, desired signal will be distorted since power lines frequency might contain components of the desired SEMG signal [23]. Hence some literature does not recommend the use of notch filter [12]. In spectrum interpolation method, given an SEMG signal, true power spectrum of certain frequency in that signal can be estimated by interpolation of the curve at that frequency. Thus method is like a notch filter with limited attenuation instead of infinite null [23]. In [21] adaptive filtering is developed aimed to remove both power lines and ECG artifact interference.

There are numerous other literatures regarding noise and artifact removal from SEMG signal using methods that have been discussed above. Some recent literatures on this area are removing electromagnetic noise from single electrode SEMG signal [25] and the use of digital Butterworth filter to subtract noise from low magnitude SEMG using simulated EMG signal [26]. Some literatures have used neural network for EMG noise removal [27], [28].

III. SEMG Signal Analysis

A. Amplitude Estimation

SEMG signal can be analyzed by its amplitude estimation. EMG signal exhibits nonlinearity. Its amplitude at any instant in time is stochastic and unpredictable and it fluctuates very rapidly between positive and negative values. In digital signal processing, the fluctuations could be removed by obtaining the average of the random values which is analogous to smoothing operation in analog processing. Since the signal fluctuates between positive and negative it produces meaningless results. Therefore rectification of the EMG signal is necessary before averaging. Full-wave rectification is preferred to half- wave so that all energy of the signal is taken into account [29].

Study of amplitude estimation of EMG signal had become an important parameter for feature extraction. As early as 1952, the first continuous EMG amplitude estimator is mentioned in the literature [30]. It is a classical hardware approach where signal is full-wave rectified before it is low pass filtered using resistor-capacitor. Nowadays signal analysis is computed digitally on a processor or using some software. Many techniques are available these days which had proven to be more efficient than the traditional approach.

To analyze the amplitude of EMG signal, parameters that are frequently used are root mean square (RMS) and mean absolute value (MAV). RMS is square root of average power of a signal for a given period of time. MAV on the other hand is area under the signal. As the name implies, MAV only takes the absolute value of the amplitude. Thus, the EMG signal is rectified before MAV is computed. RMS is usually preferred than MAV as it involves a measure of the power. Also, the assumption that probability density of surface EMG is Gaussian had made RMS to be the maximum likelihood estimator of EMG amplitude [31]. When EMG signal is modeled as Laplacian, MAV is comparable to RMS [32]-[33].

Graupe and Cline [34] introduced temporal whitening followed by 245 ms window of moving average root mean square (MARMS) had been implemented in some literatures to obtain the amplitude estimate [35]-[36]. Comparing the result with the traditional amplitude estimator described in [30], MARMS with temporal whitening filter shows major improvement in SNR performance. While previous studies deal with stationary EMG signal using fixed window length for smoothing, now researchers give stress to work on dynamic EMG where exerted force or muscle length changes during contraction and frequency content of the signal continuously changes with time. To estimate the amplitude of dynamic EMG, adaptive smoothing window length had been proposed [37]. In this work, simulation and experimental results conclude that the advantage of adaptive processor is found to be situation dependent. Meaning that in only certain cases, adaptive window length might have advantage over fixed- length.

B. Time Analysis

1. Turns per second (t/s): Number of slope reversals per second separated from the previous and the following turn by an amplitude difference greater than 20 μV.
2. Zero crossings per second (zc/s): Defined as the number of sign reversals exceeding a threshold of 20 μV per second.

C. Frequency Analysis

SEMG signal being non stationary can also be evaluated by means of analyzing the frequency spectrum. After obtaining the frequency spectrum, the signal is assessed by the measurements of parameters like power spectral density (PSD) and its two variables mean and median frequency.

1. Power Spectral Density: Amount of power per unit of frequency as a function of the frequency. The power spectral density is the Fourier transform of the autocorrelation sequence. It is the square of the Fourier Transform of EMG signal divided by the signal length. PSD shows how power of signal in time series is distributed with frequency.
2. Mean Frequency: It is an average power. It is the frequency dividing the area under the power spectral (PS) curve in two equal parts. It is also known as centroid frequency.

$$\text{Mean frequency} = \sum_{j=1}^{M} fiPj / \sum_{j=1}^{M} Pj'$$

3. Median Frequency: It is the frequency at which the EMG power spectrum is divided into two regions with equal power or amplitudes. It is the half of the total power.

$$\text{Median frequency} = \sum_{j=MD}^{M} Pj = 1/2 \sum_{j=1}^{M} Pj$$

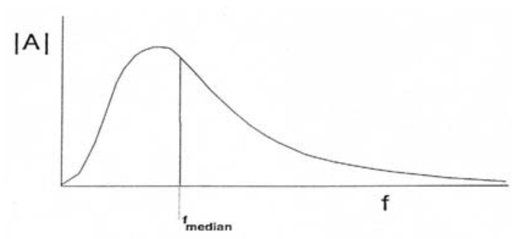

Fig. 3 Power spectral density and Median frequency

There is no clear definition of mean and median frequency except to define it by mathematical equation. The SEMG is analyzed statistically and the result of frequency analysis is often used, involving samples of data from a number of subjects [38]. Frequency analysis is also used in the study of muscle fatigue [39].

D. Time-Frequency Analysis

Time-frequency analysis is the most suitable technique for analyzing non-stationary signals like SEMG. As noted by Jean Ville in 1947, there are two basic approaches to time-frequency analysis. The first approach is to cut the signal into slices in time, and then to analyze separately each of these slices to examine their frequency content. The other approach is to first filter out different frequency bands, and then cut these bands into slices in time and analyze their energy content. The first one is used for transforms like short time Fourier transform and the Wigner-Ville transform, while the second one is used for the wavelet transform.

The time-frequency approach on SEMG signal had been studied and applied by researchers with implementation of various techniques like Cohen Class Transform, Short Time Fourier Transform (STFT) [40], [41], Wigner-Ville Distribution (WVD) [42]-[44], Choi-Williams Distribution [45] and Wavelet Transform [46].

Fourier Transform is the most popular method used for frequency analysis of time domain signals. It is suitable for stationary signals where frequency components do not vary with time. But, for non stationary signals there are various components of frequency at different instants of time. SEMG signal is a non-stationary type signal.

The wavelet transform is used to decompose a signal into its constituent parts (wavelet functions) and then analyzing it in different frequency domains with each components resolution matched to its scale. Thus a correlation between the time and frequency domains of a non-stationary signal is established.

Comparison between different methods of time-frequency approach on SEMG signal had been studied and reported in several literatures. WT was compared with STFT and WVD and it was found that WT had good resolution and high performance for myoelectric signals [46]. Cohen class transformation was particularly suitable for analyzing surface myoelectric signals [47]. WT can be used to analyze signals at different multiresolution levels. The relationships between wavelet coefficients and time frequency plane was also analysed [48]. Wavelet function is both dilated and translated in the time and cross-correlated with the time domain SEMG signal [49]. STFT, Running Windowed Exponential Distribution (RWED), Pseudo Wigner-Ville distribution (PWVD) and Continuous Wavelet transform (CWT) were compared and it was found that first three methods were poor in achieving good time and frequency resolution but CWT was very reliable in analysis of bioelectrical signals in general and showed better statistical performance than other three methods [50].

IV. Applications Of SEMG

A. Estimation of Muscle Fiber Conduction Velocity

Action potential propagates through nerve fiber with velocity known as nerve conduction velocity (NCV). In case of muscle, it is called muscle fiber conduction velocity (MFCV) and is dependent on diameter and type of the fiber itself. SEMG is useful in estimating the value of MFCV. Average delay between SEMG signals recorded from two or multi channel is used to estimate MFCV. Location of electrodes for recording is in the way that the propagation moves along the fiber between the electrodes. Various literatures have reported studies on MFCV using SEMG. Studies had been done either for medical diagnosis or to study the characteristics of MFCV. Techniques for MFCV estimation had been a subject of interest with a number of approaches had been proposed such as the use of two-dimensional SEMG recording [51], regression analysis between spatial and temporal frequencies of multiple dips introduced in the EMG power spectrum [52] using normalized peak-averaging technique [53] and minimization of the mean square error between time-filtered versions of two surface EMG signals [54].

B. Prosthetic Device

Prosthetic devices are often used to replace the missing parts of human body. Various type of input to the device for mean of control had been used by the researchers. Bioelectrical signals such as evoked potential (EP), nerve conduction velocity (NCV), EEG, EMG, EOG fit well as an input for prosthetic device control.

Myoelectric control uses the EMG generated by muscular contractions as an input to controllers for powered prostheses for many years. For the purpose of prosthetic control surface electrodes are equally beneficial as intramuscular electrodes [55]. Numerous literatures had been reported regarding studies in this area. EMG controlled prosthetic device is developed by analysing signal for discrimination, classification, pattern recognition or feature extraction [56]-[58]. By employing pattern recognition lots of control information can be extracted from SEMG signal. In terms of SEMG feature extraction method, various techniques have been reported in literatures. In general there are two categories of feature extraction techniques one in time domain and another one in time-frequency domain. Often researchers choose to implement multiple techniques and then to select the most suitable one. In one literature, for feature extraction wavelet packet transform was used and for dimensionality reduction and nonlinear mapping of the features, linear, nonlinear feature projection method was proposed comprising of PCA and SOFM [59]. In another literature, various feature sets consisting of Slope Sign Changes (SSC), Number of Zero Crossings (ZC), Waveform Length (WL), Hjorth Time Domain (HTD) Parameters, Sample Skewness (SS), and Auto Regressive (AR) Model from the EMG signals were extracted. These features were then reduced in dimensionality with the Linear Discriminant Analysis (LDA) feature projection [60]. It is proved that feature projection methods can consolidate such information more effectively than feature selection based methods in EMG classification problems [61].

For developing prosthetic device for amputees, SEMG data is to be acquired from the respective subjects to analyze the SEMG signal characteristic. Data can be taken from muscles located at residual part of the limb where the prosthetic device is attached to [7]. Remnant of the muscles in residual limb is likely linked with muscles of the lost limb. The type of prosthetic device ensures the location of surface electrode on muscles for SEMG acquisition. For instance, for prosthetic hand, extensor carpi ulnaris and flexor carpi ulnaris located on the forearm are the recommended spot for electrode placement [62], [63]. For studying the characteristics of different types of movement, requires a much complex design and more electrodes might be needed to obtain more information. Prosthetic hand complete with fingers is an example of such a design. Decoding of individuated finger movements had used up to 32 electrodes attached on different area of forearm [64]. DSP-based controller for prosthetic hand had been used for pattern recognition. Here eight parameters were computed for SEMG feature extraction which were integral of EMG, waveform length, variance, zero crossings, slope sign changes, Willison amplitude, cepstrum analysis and autoregressive model. The parameters were grouped into four groups and combined with each other in the classification stage to choose the highest classification rate before the selected feature is implemented in the PC based discriminative system [65]. Different techniques have been implemented by researchers in their literatures depending on the task to be performed. For example, in a work on developing fingers movement of prosthetic hand, time-domain features performed better in real-time decoding of hand and wrist movements [64], [66], [67]. Another work on prosthetic hand used both time and time-frequency domain for feature extraction and implemented the result on a neuro-fuzzy system for pattern recognition [68].

In contrast to conventional hardware, an Evolvable Hardware (EHW) chip had been designed as a controller for myoelectric prosthetic hand which adapts to changes in task requirements or changes in the environment, through its ability to reconfigure its own hardware structure dynamically and autonomously. The chip consisted of Genetic Algorithm (GA) hardware, reconfigurable hardware logic, a chromosome memory, a training data memory and a 16-bit CPU core (NEC V30) [69]. Another two-step incremental EHW is based on designing controllers for prosthetic hand providing six different motions in three different degrees of freedom: Open and Close hand, Extension and Flexion of wrist, Pronation and Supination of wrist [70].

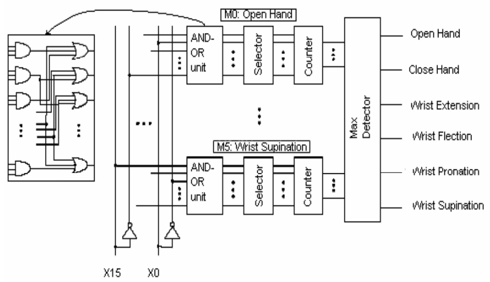

Fig. 4 The digital gate based architecture of the prosthetic hand controller

C. Clinical Diagnosis

SEMG has been used effectively for functional electrical stimulation (FES) or for the controlling of artificial limbs, but its use in clinical diagnosis has been very limited or non-existent. SEMG should not be used as a diagnostic tool due to the phenomenon of crosstalk, signal attenuation and filtering [3]. Several review reports regarding the reliability of SEMG technique for diagnostic purpose are available. SEMG generated by either voluntary or electrically elicited muscle activity, contain more significant information than it was originally believed had been proved in number of studies [4]. One of the problems with SEMG when used as diagnostic tool is the difficulties in extracting features of single motor units which is necessary for diagnosis of neuromuscular disorders [71]. Since electrode placement is important for obtaining the SEMG signal with maximum information from the muscle, improved methods for achieving appropriate electrode placement will enhance outcomes based on the signal. A multiple surface electrode had been designed with capabilities to detect electrical activity of muscle up to single motor units [72], [73]. Several recording technique that used such type of electrode had been introduced. High density-surface EMG (HD-SEMG) uses multiple closely spaced electrode overlying restricted area of skin but had not been widely used as diagnostic tools in clinical neurophysiology practices [74]. In one of the literature, HD-SEMG technique had been tested for clinical application on detecting post-poliomyelitis syndrome by comparing the SEMG between healthy subjects and those with the syndrome. The result of raw signal analysis had shown significant differences between the groups [75]. Based on outcome of this literature, the authors had urged that more studies should be initiated to explore the diagnostic value of SEMG. In another literature, a high-spatial-resolution surface EMG (HSR-EMG) is mentioned which used multiple-electrode array combined with spatial filter procedure [76]. A number of recent studies that make use of multiple surface electrodes for clinical application had been reported in literatures. For example, investigation of motor unit characteristics of biceps brachii done on post-stroke patients [77], investigation on SEMG signal in carpal tunnel syndrome to observe alteration on the signal [78] and analysis of interspike interval in neuromyotonia syndrome [79].

D. Biomechanics and Motion Analysis

SEMG is well suited into studies of motion, gait analysis or body movements. A monopolar or bipolar electrode is sufficient for this purpose. The challenge is perhaps to deal with anomaly in signals due to noises or motion artifact. It can be used in almost all type of works concerning muscle movement, not only the limbs but also face [80], [81] and on both human and animals [82]. Pattern classification can be used for walking motions [83]. In sports science, movement and motion are always been a subject of study. Data from SEMG is used to obtain statistical analysis result for various purposes which includes study in possibilities of injury [84], effect of different skills of sports on neuromuscular activity [85], effect of detraining [86], examination on rapid muscle force characteristics after high level match play [87], quantification of muscle activation pattern of certain activities involving movement [88], for different walking speed of normal healthy individuals. The potential use of this analysis is in controlling the prosthetic device like artificial knee or hand. A human may deviates from his normal gait because of neurological, anatomical and environmental reasons and to correct an individual's gait, an accurate and quantitative assessment of deviation is required. There are many techniques which have developed over the years. A contact based method was developed in which sensors like electro-goniometer and accelerometer were attached to individual's limb and their movement was recorded. But the sensor hinders the normal movement and the information available is limited. Later, non-contact or imaging based methods were developed using a camera system [89]. Magnitude and intensity of the EMG signal was qualitatively related to the force produced by a muscle under given condition. Guidelines for designing envelope filters and specifying the number of strides needed to produce valid EMG profiles [90] just to name a few.

E. Speech Recognition

Speech recognition has become a widely researched field covering tasks such as autonomous transcription on a home computer to advanced military and security applications. One proposed function is the control of secondary tasks in military fighter jets. Due to the complexity of their instrument panels and controls, pilots are forced to place a large portion of their focus downwards. It is desirable to implement a speech recognition system that would alleviate some of this dependence and enable more concentration to be shifted towards “heads-up” flying. However in order for speech recognition to be a usable tool in such a critical function, accuracy rates must be exceptional [91]. The idea is to research alternative control technologies to aid pilots in the operation of high performance aircraft and to develop speech prosthesis that function using the myoelectric signal as input. The cockpit of an aircraft is an environment of high audio noise but the myoelectric signals are unaffected [92]. The idea in developing an EMG based automatic speech recognition (ASR) system is based on assumption that articulatory facial muscles might contain some kind of speech information. Movement of lips or jaw during speech production is obviously synchronized with contraction and relaxation of certain facial muscles. Thus, SEMG signal acquired from these facial muscles, if it contain unique characteristic according to the corresponding speech signal, could provide an alternative ASR system which is advantageous when applied in a noisy environment. The result showed that SEMG based speech recognition was a promising way towards an ASR system [93].

Several literatures had initiated study in this particular area. Artificial neural network was used for classification of speech based on SEMG signal. This study involved three facial muscles: mentalis, depressoranguli oris and massetter [94]. Multi-stream Hidden Markov Model (HMM) for EMG-based speech recognition was implemented where no voice generation involve, only movement of mouth. Another recent work had also used the Hidden Markov Model to model the SEMG signal for certain Korean words [95], [96]. Work has been also done on unvoiced digital Chinese recognition based on facial myoelectric signal. Genetic arithmetic and support vector machine classifier had been used [97].

V. Discussion

SEMG signal proved to be a useful tool for various applications in clinical diagnosis, sport science for performance improvement and injury detection, muscle fatigue, gait analysis and human-computer interface for prosthetic device and speech recognition. Although there is some argument on effectiveness for use in diagnostic purpose, recent developments on surface electrode design had brought to a promising future of SEMG for clinical application. Other than this, there are a lot of other applications in which SEMG could be implemented. For example, in control of robotic arm for industrial purpose, to characterize hand gesture recognition which might be useful in sign language [98], design of wheel chair based on SEMG signal [99] or to develop an emotion recognition system [100].

However, in order to employ SEMG, one still had to consider the effectiveness of the SEMG recording equipments. The number of electrodes sometimes could be crucial. To obtain details of different movement such as in prosthetic fingers, sufficient number of electrodes has to be attached on the forearm. Record from each location of muscles that involve in movement of fingers is important to provide different type of features. Another crucial aspect is the knowledge of analysis technique of SEMG signal to obtain its features. While utilizing SEMG as a tool, its features and characteristic is the key to information which then linked with the outcome of the study. Sometimes, features provided by SEMG obtained from numerous subjects are gathered to obtain some hypothesis according to the interest of the study. Applications like biomechanics and motion study make use of statistical analysis. Analysis methods of SEMG are classified into amplitude, time domain, frequency domain and time-frequency domain. It is up to the researcher to select the most reliable, but often more than one method is implemented to provide variety in results.

VI. Conclusion

Study on SEMG is very broad, ranging from the design of electrodes, recording techniques, analysis methods and applications. Because of its non-invasive nature, it can be utilized for clinical diagnosis making it much more comfortable for subjects. But still there is a lot to improve in the design of recording equipments especially design of electrodes so that SEMG could be fully reliable for clinical purpose. However, for certain applications like human computer interface, muscle fatigue, gait analysis basic requirement of recording equipment is sufficient.

References

[1] J. V. Basmajian and C.J. De Luca, "*Muscles Alive: Their Function Revealed by Electromyography*" Baltimore: Williams & Wilkens, 1985.

[2] M. B. I. Raez, M.S. Hussain, and M. Yasin, "Techniques of EMG signal analysis: detection, processing, classification and applications", *Biological Procedures Online*, vol. 8, pp. 11–35, 2006.

[3] S.L. Pullman, D.S. Goodin, A.I. Marquinez, S.Tabbal, and M. Rubin, "Clinical utility of surface EMG: Report of the therapeutics and technology assessment subcommittee of the American Academy of Neurology," *Neurology*, vol. 55, pp. 171-177, 2000.

[4] Merletti R. and De Luca C. J., "New Techniques in surface electromyography. In: Desmedt J.E. (Ed.)", *Computer-Aided Electromyography and Expert Systems, Elseveir* pp. 115-124, 1989.

[5] V. Gupta, N. P. Reddy, and E. P. Canilang, "Surface EMG Measurements at the Throat during Dry and Wet Swallowing", *Dysphagia*, vol. 11, pp. 173-179, 1996.

[6] W. Peasgood, T. Whitlock, A. Bateman, M.E. Fry, R.S. Jones, and A. Davis-Smith, "EMG-controlled closed loop electrical stimulation using a digital signal processor," *Electronics Letters*, vol. 36, pp.1832-1833, 26th October 2000.

[7] N.M.L Celani, C.M. Soria, E.C. Orosco1, F.A. di Sciascio, and M E. Valentinuzzi, "Two-Dimensional Myoelectric Control of a Robotic Arm for Upper Limb Amputees", *Journal of Physics: Conference Series*, vol. 90, pp. 1-8, 2007.

[8] A. Bhaskar, E. Tharion and, S.R. Devasahayam, "Computer-based inexpensive surface electromyography recording for a student laboratory", *American Journal of Physiology -Advances in Physiology Education*, vol. 31, pp. 242-243, 2007.

[9] "*Surface Electromyography: Detection and Recording*," DelSys Incorporated, 1996.

[10] S.W. Johnson, P.A. Lynn, J.S.G. Miller and G. A. L. Reed, "Miniature skin-mounted preamplifier for measurement of surface electromyographic potentials", *Medical and Biological Engineering and Computing*, vol. 15, pp. 710-711, 1977.

[11] K. Najarian and R. Splinter, "Chapter 11: Electromyogram" *in Biomedical signal and image processing, CRC Press*, pp.237-256, 2006.

[12] R. Merletti and H.J. Hermens, "Detection and conditioning of surface the EMG signal," in *Electromyography: physiology, engineering, and noninvasive applications*, R. Merletti, and P.A. Parker, Eds. Wiley-IEEE, 2004, pp. 107-132.

[13] A. Fratini, M. Cesarelli, P. Bifulco, A. La Gatta, M. Romano, and G. Pasquariello, "Acceleration driven adaptive filter to remove motion artifact from EMG recordings in Whole Body Vibration", *IFMBE Proceedings MEDICON*, pp. 990-993, 2007.

[14] G.T. Allison, "Trunk muscle onset detection technique for EMG signals with ECG artifact," *Journal of Electromyography and Kinesiology*, vol. 13, pp. 209-216, 2003.

[15] Y. Hu, X.H. Li, X.B. Xie, L.Y. Pang, Y. Cao, and K.D.K.Luk, "Applying independent component analysis on ECG cancellation technique for the surface recording of trunk electromyography," *IEEE EMBS 27th Annual International Conference of the Engineering in Medicine and Biology Society*, pp. 3647-3649, 2005.

[16] Y. Hu, J.N.F. Mak and K.D.K. Luk, "Effect of electrocardiographic contamination on surface electromyography assessment of back muscles", *Journal of Electromyography and Kinesiology*, vol. 19, pp. 145-156, 2009.

[17] C. Marque, C. Bisch, R. Dantas, S. Elayoubi, V. Brosse, and C. Pe´rot, "Adaptive filtering for ECG rejection from surface EMG recordings", *Journal of Electromyography and Kinesiology*, vol. 15, pp. 310-315,2005.

[18] S. Redfern, R.E. Hughes, and D.B. Chaffin, "High-pass filtering to remove electrocardiographic interference from torso EMG recordings", *Clinical Biomechanics*, vol. 8, pp. 44-48, 1993.

[19] J. D. M. Drake and J. P. Callaghan, "Elimination of electrocardiogram contamination from electromyogram signals: An evaluation of currently used removal techniques," *Journal of Electromyography and Kinesiology*, vol. 16, pp. 175-187, 2006.

[20] P. Zhou, B. Lock, and T.A. Kuiken, "Real time ECG artifact removal for myoelectric prosthesis control," *Physiological Measurement*, vol.28, pp. 397-413, 2007.

[21] S. Yacoub and K. Raoof, "Noise Removal from Surface Respiratory EMG Signal", *International Journal of Computer Information and Systems Science and Engineering*, vol. 2, pp. 226-233, 2008.

[22] K.S. Cheng and W.Y. Yang, "Using adaptive filter for extracting the surface diaphragmatic EMG signal," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, vol. 14, pp. 2604-2605, 1992.

[23] D. T. Mewett, K.J. Reynolds, and H. Nazeran, "Reducing power line interference in digitised electromyogram recordings by spectrum interpolation", *Medical and Biological Engineering and Computing*, vol. 42, pp. 524-531, 2004.

[24] S. Yacoub and K. Raoof, "Power line interference rejection from surface electromyography signal using an adaptive algorithm", *IRBM*, vol. 29, pp. 231-238, 2008.

[25] T.W. Beck, J.M. Defreitas, J .T. Cramer and J.R. Stout, "A comparison of adaptive and notch filtering for removing electromagnetic noise from monopolar surface electromyographic signals", *Physiological Measurement*, vol. 30, pp. 353-361, 2009.

[26] R.G.T. Mello, L.F. Oliveira, and J. Nadal, "Digital Butterworth filter for subtracting noise from low magnitude surface electromyogram", *Computer Methods and Programs in Biomedicine*, vol. 87, pp. 28-35,2007.

[27] S.N. Kale and S.V. Dudul, "Intelligent Noise removal from EMG signal using Focused Time Lagged Recurrent Neural Network", *Applied Computational Intelligence and Soft Computing*, pp. 1-12, 2009.

[28] V.R. Mankar and A.A. Ghatol, "Use of RBF neural network in EMG signal noise removal", *WSEAS Transactions on Circuits and Systems*, pp. 259-265, 2008.

[29] C.J. De Luca, "*Electromyography in Encyclopedia of Medical Devices and Instrumentation*", vol. 2, J.G. Webster, Ed. USA: John Wiley and Sons Inc., 1988, pp. 1111-1120.
[30] V. T. Inman, H. J. Ralston, J. B. de C. M. Saunders, B. Feinstein, and E.W. Wright, "*Relation of human electromyogram to muscular tension,"* EEG Clinical Neurophysiology, vol. 4, pp. 187-194, 1952.
[31] N. Hogan and R. W. Mann, "Myoelectric signal processing: Optimal estimation applied to electromyography -Part I: Derivation of the optimal myoprocessor," *IEEE Transactions on Biomedical Engineering, vol. BME-27*, pp. 382-395, 1980.
[32] Y. St-Amant, D. Rancourt, and E. A. Clancy, "Influence of smoothing window length on electromyogram amplitude estimates", *IEEE Transactions on Biomedical Engineering*, vol. 45, pp. 795–800, 1998.
[33] E. A. Clancy and N. Hogan, "Probability Density of the Surface Electromyogram and its Relation to Amplitude Detectors," *IEEE Transactions on Biomedical Engineering*, vol. 46, pp.730–739, 1999.
[34] Graupe D. and Cline W. K., "Functional separation of EMG signals via ARMA identification", *IEEE Trans Syst. Man. Cybern*, vol. 5, pp 252-259, 1975.
[35] E. A. Clancy and N. Hogan, "Single Site Electromyograph Amplitude Estimation," *IEEE Transactions on Biomedical Engineering*, vol. 41, pp. 159–167, 1994.
[36] E. A. Clancy and N. Hogan, "Multiple Site Electromyograph Amplitude Estimation", IEEE Transactions on Biomedical Engineering, vol. 42, pp. 203–211, 1995.
[37] E. A. Clancy, "Electromyogram Amplitude Estimation with Adaptive Smoothing Window Length," *IEEE Transactions on Biomedical Engineering*, vol. 46, pp. 717–729, June 1999.
[38] S. Karlsson and B. Gerdle, "Mean frequency and signal amplitude of the surface EMG of the quadriceps muscles increase with increasing torque - a study using the continuous wavelet transform," *Journal of Electromyography and Kinesiology*, vol. 11, pp. 131-140, 2001.
[39] S. Boyas, O. Maïsetti, and A. Guével, "Changes in sEMG parameters among trunk and thigh muscles during a fatiguing bilateral isometric multi-joint task in trained and untrained subjects", *Journal of Electromyography and Kinesiology*, vol. 19, pp. 259-268, 2009.
[40] L.Y. Cai, Z.Z. Wang, and H.H. Zhang, "A surface EMG signal identification method based on short-time Fourier transform," *Chinese Journal of Medical Instrumentation*, vol. 24, pp. 133-136, March 2000.
[41] P.J. Sparto, M. Parnianpour, E.A. Barria, and J.M. Jagdeesh, "Wavelet and short-time fourier transform analysis of electromyography for detection of back muscle fatigue," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 433-436, 2000.
[42] A.L. Ricamato, R.G. Abshe, M.T. Moffroid, and J .P. Tranowski, "A time-frequency approach to evaluate Electromyographic recordings", *Proceedings - Fifth Annual IEEE Symposium on Computer-Based Medical Systems*, pp. 520-527, 1992.
[43] G.C. Jang, C.K. Cheng, J.S. Lai, and T.S. Kuo, "Using Time-Frequency Analysis Technique in the Classification of Surface EMG Signals," *Proceedings of the 16th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1242-1243, 1994.
[44] C.M. Potes, "Assessment of Human Muscle Fatigue from Surface EMG Signals Recorded during Isometric Voluntary Contractions", *IFMBE Proceedings - 25th Southern Biomedical Engineering Conference*, pp. 267-270, 2009.
[45] P. Bonato, G. Gagliati and M. Knaflitz, "Analysis of myoelectric signals recorded during dynamic contractions a time frequency approach to assessing muscle fatigue," *IEEE Engineering in Medicine and Biology Magazine*, vol. 15, pp. 102–111, 1996.
[46] N. M. Sobahi, "Denoising of EMG Signals Based on Wavelet Transform", *Asian Transactions on Engineering*, vol. 01 no. 05 pp 17-23, 2011.
[47] Cohen L. "*Time-frequency analysis*", Englewood Cliffs, Prentice-Hall; New Jersey, USA, 1995.
[48] Pattichis C. S, Pattichis M.S. Time-scale analysis of motor unit action potentials. *IEEE Trans Biomed Engg* vol. 46, no. 11, pp 1320-1329, 1999.
[49] Kumar D K, Pah N D, Bradley A., "Wavelet analysis of surface electromyography to determine muscle fatigue. *IEEE Trans Neural Syst Rehabil Eng*. vol. 11, no. 4, pp 400-406.
[50] S. Karlsson, Y. Jun, and M Akay, "Time-frequency analysis of myoelectric signals during dynamic voluntary contractions: a comparative study," *IEEE Transactions on Biomedical Engineering*, vol. 47, pp. 228–238, 2000.
[51] D. Farina, W. Muhammad, E. Fortunato, G. Meste, R. Merletti and H. Rix, "Estimation of single motor unit conduction velocity from surface EMG signals detected with linear electrode arrays", *Med. Biol. Eng. Comput*., vol. 39, pp 225-236, 2001.
[52] D. Farina and F. Negro, "Estimation of Muscle Fiber Conduction Velocity With a Spectral Multidip Approach," IEEE *Transactions on Biomedical Engineering*, vol. 54, pp. 1583 – 1589, Sept. 2007.
[53] K. Nishihara, K. Hosoda, and T. Futami, "Muscle fiber conduction velocity estimation by using normalized peak-averaging technique", Journal of Electromyography and Kinesiology, vol. 13, pp. 499-507, 2003.
[54] E.N. Kamavuako and D. Farina, "Estimation of muscle fiber conduction velocity of doublet discharges", *Biomedical Signal Processing and Control*, vol. 2, pp. 331-338, 2007.
[55] Erik J. Scheme, Bernard Hudgins and Phillip A.Parker, "Myoelectric Signal Classification for Phoneme-Based Speech Recognition", *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 4, 694-699, 2007.
[56] G.N. Saridis and T.P. Gootee, "EMG pattern analysis and classification for a prosthetic arm", *IEEE Transactions on Biomedical Engineering*, vol. 29, pp. 403-412, 1982.
[57] Z.-K. Mahyar, B.C. Wheeler, K. Badie, and R.M. Hashemi, "EMG feature evaluation for movement control of upper extremity prostheses," *IEEE Transactions on Rehabilitation Engineering*, vol. 3,pp. 324-333, 1995.
[58] H.P. Huang and C.Y. Chen, "Development of a myoelectric discrimination system for a multi-degree prosthetic hand", *Proceedings of The IEEE International Conference on Robotics and Automation*, pp. 2392-2397, 1999.
[59] Chu J.U., Moon I. and Mun M.S., "A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand*", IEEE Transaction on Biomedical Engineering*, vol. 53, no. 11, pp 2232-2239, 2006.
[60] Rami N. Khushaba, Sarath Kodagoda, Maen Takruri, Gamini Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals", *Expert Systems with Applications*, vol. 39, pp 10731–10738, 2012.
[61] K. Englehart, B Hudgins, P. A. Parker and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representation", *Medical engineering and Physics*, vol. 21, pp 431-438, 1999.
[62] Z.Z. Luo and G.Y. Yang, "Study of Myoelectric Prostheses Based on Fuzzy Control and Touch Feedback" *International Conference on Neural Networks and Brain - ICNN&B '05*, pp. 1815-1819, 2005.
[63] G.Y. Yang, "Study of Myoelectric Prostheses Hand based on Independent Component Analysis and Fuzzy Controller," *8th International Conference on Electronic Measurement and Instruments-ICEMI '07*, pp. 1-174 – 1-178, 2007.
[64] F.V.G. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N.V. Thakor, "Decoding of Individuated Finger Movements Using Surface Electromyography", *IEEE Transactions on Biomedical Engineering*, vol. 56, pp. 1427-1434, May 2009.
[65] H.P. Huang and C.Y. Chiang, "DSP-Based Controller for a Multi-Degree Prosthetic Hand", Proceedings - *IEEE International Conference on Robotics and Automation - ICRA '00*, pp. 1378-1383, 2000.
[66] F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings and N.V. Thakor, "Towards the control of individual fingers of a prosthetic hand using surface EMG signals," *Conference Proceedings: 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 6146-6149, 2007.
[67] R.J. Smith, F. Tenore, D. Huberdeau, R. Etienne-Cummings, and N.V. Thakor, "Continuous decoding of finger position from surface EMG signals for the control of powered prostheses," *Conference Proceedings : 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 197-200, 2008.
[68] M. Khezri, M. Jahed, and N. Sadati, "Neuro-fuzzy surface EMG pattern recognition for multifunctional hand prosthesis control," *IEEE* International Symposium on Industrial Electronics, pp. 269-274, 2007.
[69] I. Kajitani, M. Murakawa, D. Nishikawa, H. Yokoi, N. Kajihara, M. Iwata, D. Keymeulen, H. Sakanashi and T. Higuchi, "An evolvable hardware chip for prosthetic hand controller", *Proceedings of the Seventh International Conference on Microelectronics for Neural, Fuzzy, and Bio-Inspired systems*, pp 179-186, 1999.
[70] J. Torresen, "Two step incremental evolution of a prosthetic hand controller based on digital Logic gates", *ICES- 2001*, pp 1-13.

[71] M. J. Zwarts, G. Drost and D.F. Stegeman, "Recent progress in the diagnostic use of surface EMG for neurological diseases", *Journal of Electromyography and Kinesiology*, vol. 10, pp. 287-291, 2000.
[72] R. Merletti, D. Farina, and M. Gazzoni, "The linear electrode array: a useful tool with many applications," *Journal of Electromyography and Kinesiology*, vol. 13, pp. 37–47, 2003.
[73] J.H. Blok, J.P. Van Dijk, G. Drost, M.J. Zwarts, and D.F. Stegeman, "A high-density multichannel surface electromyography system for the characterization of single motor units," *Review of Scientific Instruments*, vol. 73, pp. 1887–97, 2002.
[74] Gan Huang, Zhiguo Zhang, Dingguo Zhang and Xiangyang Zhu, "Spatio-spectral filters for low density surface electromyographic signal classification", *Med Biol Eng Comput.* vol. 51, pp 547–555, 2013.
[75] G. Drost, D.F. Stegeman, B.G.M. van Engelen and M.J. Zwarts, "Clinical applications of high-density surface EMG: A systematic review," *Journal of Electromyography and Kinesiology*, vol. 16, pp.586–602, 2006.
[76] G. Drost, D.F. Stegeman, M.L. Schillings, H.L.D. Horemans, H.M.H.A. Janssen, M. Massa, F. Nollet, and M.J. Zwarts, "*Motor unit characteristics in healthy subjects and those with post poliomyelitis syndrome: A high-density surface EMG study*," Muscle and Nerve, vol. 30, pp. 269-276, 2004.
[77] L.A.C. Kallenberg and H.J. Hermens, "*Motor unit properties of biceps brachii in chronic stroke patients assessed with high-density surface EMG*," Muscle and Nerve, vol. 39, pp. 177-185, 2009.
[78] A. Rainoldi, M. Gazzoni and R. Casale, "Surface EMG signal alterations in Carpal Tunnel syndrome: A pilot study", *European Journal of Applied Physiology*, vol. 103, pp. 233-242, 2008.
[79] B. U. Kleine, D.F. Stegeman, G. Drost, and M.J. Zwarts, "*Interspike interval analysis in a patient with peripheral nerve hyper excitability and potassium channel antibodies*", Muscle and Nerve, vol. 37, pp.269-274, 2008.
[80] L.G. Tassinary, J. T. Cacioppo, and T. R. Geen, "A psychometric study of surface electrode placements for facial electromyographic recording: I: The brow and cheek muscle regions," Psychophysiology, vol. 26, pp. 1-16, 1989.
[81] S. Hanawa, A. Tsuboi, M. Watanabe, and K. Sasaki, "EMG study for perioral facial muscles function during mastication," *Journal of Oral Rehabilitation*, vol. 35, pp. 159-170, 2008.
[82] F. Biedermann, N.P. Schumann, M.S. Fischer, M.S., and H. Ch. Scholle, "Surface EMG-recordings using a miniaturised matrix electrode: A new technique for small animals," *Journal of Neuroscience Methods*, vol. 97, pp. 69-75, 2000.
[83] Ho-Lim Choi, Hee-Jung Byun, Won-Gyu Song, Jun-Won Son, Jung-Tae Lim, On pattern classification of EMG signals for walking motions". *Artif. Life Robotics*, vol. 4, pp 193-197, 2000.
[84] E.J. Cowling and J.R. Steele, "Is lower limb muscle synchrony during landing affected by gender? Implications for variations in ACL injury rates", *Journal of Electromyography and Kinesiology*, vol. 11, pp. 263-268, 2001.
[85] A. Kaygusuz, F. Meric, K. Ertem, H. Duzova, Y. Karakoc, and C.Ozcan, "The effects of different skill training on neuromuscular electric activity of the limbs in amateur sportsmen," *Isokinetics and Exercise Science*, vol. 13, pp. 175-178, 2005.
[86] T. Hortobagyi, J.A. Houmard, J.R. Stevenson, D.D. Fraser, R.A. Johns, and R.G. Israel, "The effects of detraining on power athletes," *Medicine and Science in Sports and Exercise*, vol. 25, pp. 929-935, 1993.
[87] B. Thorlund, P. Aagaard, and K. Madsen, "Rapid muscle force capacity changes after soccer match play," *International journal of sports medicine*, vol. 30, pp. 273-278, 2009.
[88] G. Wu, W. Liu, J. Hitt, and D. Millon, "Spatial, temporal and muscle action patterns of Tai Chi gait", *Journal of Electromyography and Kinesiology*, vol. 14, pp. 343-354, 2004.
[89] Nissan Kunju, Neelesh Kumar, Dinesh Pankaj, Aseem Dhawan, Amod Kumar, "EMG Signal Analysis for Identifying Walking Patterns of Normal Healthy Individuals", *Indian Journal of Biomechanics*, 2009.
[90] R. Shiavi, C. Frigo, A. Pedotti, "Electromyographic signals during gait: Criteria for envelope filtering and number of strides", *Med. Biol. Eng. Comput.* vol. 35, pp 171-178, 1998.
[91] Erik J. Scheme, Bernard Hudgins and Phillip A.Parker, "Myoelectric Signal Classification for Phoneme-Based Speech Recognition", *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 4, 694-699, 2007.
[92] A. D. C. Chan, K.Englehart, B. Hudgins and D. F. Lovely, "Myoelectric signals to augment speech recognition", *Med. Biol. Eng. Comput*., pp 500-504, 2001.
[93] Adrian D. C. Chan, Kevin B. Englehart, Bernard Hudgins and Dennis F. Lovely, "Multiexpert Automatic Speech Recognition Using Acoustic and Myoelectric Signals", *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 4, 2006.
[94] S. Kumar, D. K. Kumar, M. Alemu, and M. Burry, "EMG based voice recognition", *Proceedings of the 2004 Intelligent Sensors, Sensor Networks and Information Processing Conference*, pp. 597–596, 2004.
[95] H. Manabe, Z. Zhang, "Multi-stream HMM for EMG-Based Speech Recognition," *Conference Proceedings: 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 4389 - 4392, 2004.
[96] K.S Lee, "EMG-based speech recognition using hidden Markov models with global control variables", *IEEE Transactions on Biomedical Engineering*, vol. 55, pp. 930-940, 2008.
[97] X.Q. Jia, X. Wang, J.H. Li, D. Yang, and Y. Song, "Unvoiced Chinese Digital Recognition Based On Facial Myoelectric Signal", *Proceedings of 2006 International Conference on Communications, Circuits and Systems*, pp. 598- 601, 2006.
[98] X. Chen, X. Zhang, Z.Y Zhao, J. H. Yang, V. Lantz and K.-Q. Wang, "Multiple hand gesture recognition based on surface EMG signal", *1st International Conference on Bioinformatics and Biomedical Engineering*, pp. 506-509, 2007.
[99] C. Liu and H. Wang, "The Design of Wheel chair Based on SEMG Control", *The 2nd International Conference on Bioinformatics and Biomedical Engineering*, pp. 1721-1724, 2008.
[100] C. Bo and G.Y. Liu, "Emotion Recognition from Surface EMG Signal Using Wavelet Transform and Neural Network," *The 2nd International Conference on Bioinformatics and Biomedical Engineering*, pp. 1363-1366, 2008.

Anjana Goen was born in India completed her graduation B.E. (Electronics & Telecommunication) in 1991 from Ranchi University, India and her master degree M.Tech. Telecom Technology in 2008 from RGPV, India. Now she is doing her PhD in biomedical signal processing from Jiwaji University, Gwalior, India.

She had 20 years of teaching experience. She served as lecturer in BIT Dhanbad and MITS Gwalior. Since 2000, she is an Assistant Professor at RJIT Tekanpur, Madhya Pradesh, India. She had published more than 5 papers in International Journals & Conferences. She had presented more than 10 papers in International & National Conferences. She had interest in Digital Signal and Image processing and especially in biomedical signal and image processing.

Ms Goen is life member of IETE. She had also been associated with CSI and ISTE, India.

D. C. Tiwari was born on March 8, 1952 at Gwalior, did B.Sc.(1970) and M.Sc.(1972) from Jiwaji University, Gwalior. He received CSIR (JRF) in Dec. 1972 and completed his PhD in 1976 from BITS Pilani, India. He received CSIR (SRF) and PDF in 1977. He had also carried his research work at Chelsea College London and at ERA Technology, Leatherhead, Surrey, England, 1986.

Since 1983 he is in teaching profession and from last 15 years he is Professor in School of Studies in Physics & Electronics. He served as Director Institute of Engineering, Jiwaji University and Vice Chancellor of Jiwaji university. He had published/presented about 80 papers in International & National Journal and International and National Conferences. He had special interest in plasma and microwave engineering. His interest also lies in embedded electronics and signal processing. He had completed several government projects.

Dr. Tiwari is the fellow member of IETE, life member of ISTE, CSI, India. He received German Academic Exchange Fellowship in 1984. He received best participant's lecture medal at Kolhapur in 1993. He had been awarded with best researcher's award in 2009 and with teacher's award in 2013.