

Review of Surface Electromyogram Signals: Its Analysis and Applications

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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 be 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.

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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 reject 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 μ V.
2. Zero crossings per second (zc/s): Defined as the number of sign reversals exceeding a threshold of 20 μ V 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.

$$\text{Mean frequency} = \sum_{j=1}^M f_j P_j / \sum_{j=1}^M P_j$$

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.

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

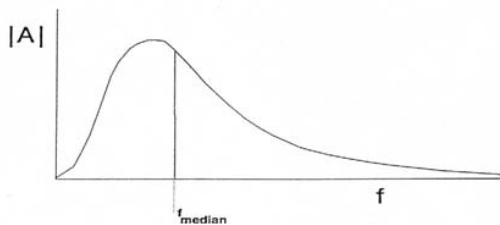


Fig. 3 Power spectral density and Median frequency

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].

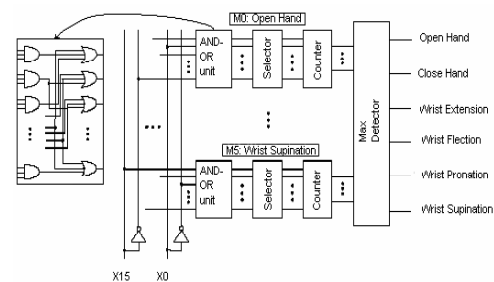


Fig. 4 The digital gate based architecture of the prosthetic hand controller

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 electrogoniometer 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 masseter [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.

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