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Surface Electromyography Signal Processing and Application: A Review

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***Abstract*- Electromyography (EMG) is a study of muscles function through analysis of electrical activity produced from muscles. This electrical activity which is displayed in 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 electromyography (SEMG) signal. During SEMG recording, several problems had to be encountered such as noise, motion artifact and signal instability. Thus, various signal processing techniques had been implemented to produce a reliable signal for analysis. There are also broad applications of SEMG signal particularly in biomedical field. The SEMG signal had been analyzed and studied for various interests such as neuromuscular disease, enhancement of muscular function and human-computer interface.**

I. INTRODUCTION

This paper will review the works on surface electromyography (SEMG) signal processing as well as the use of SEMG signal analysis for clinical application and engineering research such as prosthetic arm and speech recognition. In the beginning, this paper will briefly go through the basic theory of myoelectric signal generation. Next, the signal processing techniques applied for SEMG signal will be explained. It include methods of signal acquisition process particularly noise removal and also analysis of the signal such as amplitude and spectral analysis. This paper will also look at several works and literatures on the use of SEMG technique as a tool for various applications such as clinical diagnosis, motion analysis, prosthetic device and speech recognition. Finally, this paper would have compiled several recent works on the application of SEMG signal processing and analysis. However, it is not the objective of this paper to discuss and choose the best techniques for SEMG signal analysis since different techniques is used for a particular purpose.

II. ORIGIN OF MYOELECTRIC SIGNAL

Electromyography (EMG) is the study of muscle function through analysis of electrical potential that emanates from the muscle itself. EMG nowadays had become an important toll in

biomedical and clinical application. Thus, the detection, processing and analysis of EMG signal has 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 17^{th} century. Nevertheless, not until the last couple of decades, the EMG study had been intense due to the use of modern electronic devices and equipment along with new techniques in signal processing.

The origin of EMG is closely related to the work of nervous system. Electrochemical transmission between nerves starting from the brain produces action potential which propagates through nerve fibers. Action potential moves along nerve fiber and it will finally stimulate the skeletal muscle. This stimulation creates muscle contraction which then 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].

Representation of electrical potential in form of time varying signal is what we called as EMG signal. By studying the EMG, one is actually looking into the characteristics of body movement due to muscle contraction activity. Obtaining EMG signal from human includes several processes involving recording, data acquisition, signal conditioning and processing. Recording of EMG signal is done by mean of electrodes. Three types of electrodes that are commonly used is wire, needle and surface electrode where the latter being the most widely used since it is non-invasive [2]. With different kind of electrode, the EMG signal that obtained might contain different characteristic. That tells why the terms like 'surface EMG' and 'needle

EMG' is used in literature, that is to specify the type of electrode used for recording. Most of the literatures reviewed in this paper either specifically mention the term 'surface EMG' or clarify the use of surface electrode in its methodology.

III. SURFACE EMG SIGNAL ACQUISITION

A. Amplification

EMG signal obtained by electrode is relatively small with amplitude range up to 10 mV or ±5 mV [3,4]. This amplitude range might be too small for further processing. In most applications, EMG signal need to be digitized and sent to processor, microcontroller or CPU for feature extraction. Since signal with insufficient amplitude range might not be feasible to be analyzed, amplification of the signal is a necessity. Usually this is done with instrumentation amplifier built specifically to amplify biosignal. Prior to amplification, a pre-amplifying stage would also be necessary to provide initial amplification and 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. However it is also available in form of a special function integrated circuit (IC). Examples of instrumentation amplifier IC used in literatures are the Analog Devices AD 620 [6,7], Burr-Brown INA 102 [5] and Texas Instruments INA 128 [8]. The amplification gain varies according to amplifier manufacturer. Some literatures record an overall gain of 70,000 starts from preamplifier stage [5]. Others use smaller gain from 600, 1000 to 10,000 [9] and 50,000 [10].

B. Noise sources and removal

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 might caused by i) inherent noise in electronics equipment, ii) ambient noise from electromagnetic radiation, iii) motion artifact and iv) inherent instability of signal [11]. Noise could also originate from the electrode. The metal-electrolyte contact of electrode is intrinsically noisy and it has become an important factor in EMG noise. It is 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 [12]. Therefore, to solve the noise problem which might results from using lengthy wire, Johnson et al. (1977) had proposed a pair of surface electrode combined with differential amplifier in a single module [12]. 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 which 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 moving on skin surface and electrode wire movement. Noise produced by motion artifact is in the range of 0 to 20 Hz and the easiest way to deal with this noise is to filter it out with high-pass filter [13]. Regardless of motion artifact noises, SEMG signal in 0 to 20 Hz range do provide significant information on firing rates of active motor units [14]. 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, Fratini et al. [15] works on removing motion artifact from surface EMG record

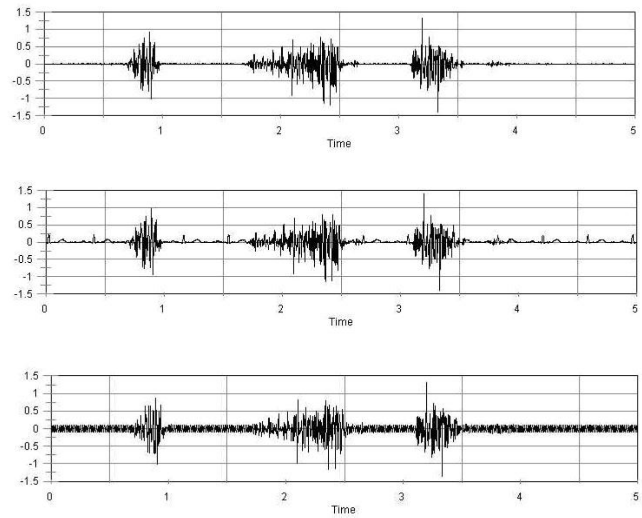

Fig. 1. Three figures showing a raw SEMG signal (above), SEMG signal with presence of small ECG artifacts (center) and SEMG signal with power line interference (below).

ings in Whole Body Vibration. Vibration training is used in sport medicine to enhance athletic performance. Surface EMG recording is done on subject undergoing vibration training for muscle activity evaluation. The vibration would produce motion artifact and creates noise. Fratini et al. [15] 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 recoding. 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 [16,17], back muscles [18,19] 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 [20,21].

However, high-pass filtering is not the only way. Zhou et al. [22] for instance had used adaptive ECG spike clipping in addition to digital high-pass filter [22]. In this work, the 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 [19][23][24]. In work by Marque et al. [19], a raw SEMG signal that contains ECG artifact is subtracted with a reference signal which is correlated with the ECG signal. The result is a denoised signal which is the estimate of the SEMG signal of interest. Marque et al. [19] conclude that adaptive filtering provides an efficient tool for ECG rejection with advantage of ability to rejects all components correlated to QRS complex.

Another source of noise in SEMG signal is the power lines with frequency of 50 or 60 Hz. For this type of noise, among methods that had been used in literatures are digital notch filter, spectrum interpolation [25] and adaptive filtering [26]. For notch filter, it could be designed with notch centered at power lines frequency and 1 Hz width. However, there is drawback with notch filter. Desired signal will be distorted since power lines frequency might contain components of the desired SEMG signal [25]. Some literature does not recommend the use of notch filter as it is not a good practice [14]. 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. This method is like a notch filter with limited attenuation instead of infinite null [25]. Adaptive filtering method for power lines noise removal had been done by Yacoub and Raoof [26]. In [23], 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. Example of recent literatures on this area are removing electromagnetic noise from single electrode SEMG signal [27] and the use of digital Butterworth filter to subtract noise from low magnitude SEMG using simulated EMG signal [28]. Also there are literatures that work on using neural network for EMG noise removal purpose [29,30].

IV. SEMG SIGNAL ANALYSIS

A. Amplitude estimation and analysis

One way to evaluate SEMG signal is by analysis of signal amplitude. EMG signal in general is a stochastic process. Its amplitude at any instant time is random where it could fluctuate between above and below zero volts and the fluctuation might be very rapid. In digital signal processing, the fluctuations could be removed by obtaining the average of the random values. It is similar to smoothing operation in analog. But, since the signal fluctuates over negative and positive value, simply averaging the signal might produce meaningless results. Thus, before this averaging task could be done, rectification of the EMG signal is necessary. Usually, full-wave rectification is preferred so that all the energy of the signal could be retained [31].

Study of amplitude estimation of EMG signal had become a distinct area. Most early literature had cited the work by Inman et al. [32] which are regarded as the first continuous EMG amplitude estimator. It is a classical hardware approach where signal is full-wave rectified before it is low-pass filtered using resistor-capacitor. Nowadays, signal analysis involves digital signal processing either by computer software or processor. More techniques had been studied that proved 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 given period of time. MAV on the other hand is area under the signal. As the name implies, MAV only engage the absolute value of the amplitude. Thus, the EMG signal had to be rectified before implementing MAV. The difference between these two parameters is that RMS involves a measure of the power of the EMG signal. Due to this fact, RMS is usually preferred than MAV. Also, assumption that probability density of surface EMG is Gaussian had made RMS to be the maximum likelihood estimator of EMG amplitude [33]. However, this is not always the case. When EMG signal is modeled as Laplacian, MAV had shown to be better than or at least as justified as RMS [34,35].

In other literatures, to obtain optimal estimation of EMG signal amplitude, temporal whitening followed by 245 millisecond window of moving average root mean square (MARMS) had been implemented [36,37]. Comparing the result with the traditional amplitude estimator described in [32], MARMS with temporal whitening filter had shown major improvement in SNR performance. While previous studies deal with stationary EMG signal using fixed window length for smoothing, much later research works on dynamic EMG where exerted force or muscle length change during contraction. To estimate the amplitude of dynamic EMG, adaptive smoothing window length had been proposed [38]. 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. Frequency Analysis

Evaluation of SEMG signal by analysis of frequency spectrum is another method that is used by researchers. Upon obtaining the frequency spectrum, the measure of the signal is assessed by parameters like power spectral density (PSD), mean frequency and median frequency. Definition for each of these parameters is:

1) Power Spectral Density: amount of power per unit of frequency as a function of the frequency. It is calculated by squaring Fourier Transform from each segment of data and then averaging them. PSD shows how power of signal in time series distributed with frequency.
2) Mean Frequency: it is related mathematically to PSD as in (1). Also known as centroid frequency.

3) Median Frequency: the frequency at which the spectrum is divided into two regions with equal power. Equation (2) shows the expression for median frequency.

$$f_{mean} = \frac{\int_0^\infty fS(f)df}{\int_0^\infty S(f)df}. \quad (1)$$

$$f_{median} = \frac{1}{2}\int_0^\infty S(f)df. \quad (2)$$

S(f) in (1) and (2) is PSD of the signal. There is no clear definition on mean and median frequency only that it is defined by mathematical equation. The result of frequency analysis often used when the SEMG that is measured is analyzed statistically, usually involving samples of data from a number of subjects [39]. Also frequency analysis is often used in study of muscle fatigue [40].

C. Time-Frequency Analysis

Fourier Transform is the most prominent method used for frequency analysis of time domain signal. It is suitable for stationary signal where all frequency components present at all time. Conversely, there is also a type of signal having various components of frequency in different instant of time. In other words, the frequency components vary with time. This type of signal is called non-stationary signal. SEMG signal is a non-stationary type signal.

Evaluation for non-stationary signal is better done with methods used for time-frequency analysis. The time-frequency approach on SEMG signal had been studied and applied by researcher with implementation of various methods such as Short Time Fourier Transform (STFT) [41,42], Wigner-Ville Distribution (WVD) [43-45], Choi-Williams Distribution (CWD) [46] and Wavelet Transform (WT) [47-50].

Comparison between different methods of time-frequency approach on SEMG signal had been studied and reported in several literatures. Canal [51] had compared WT with STFT and found that WT had good resolution and high performance for visualization of neuropathy and myopathy activity. A much wider comparison study had been done by Karlsson et al. [52]. Four methods had been used which are STFT, Running Windowed Exponential Distribution (RWED), pseudo Wigner-Ville distribution (PWVD) and continuous Wavelet transform (CWT). According to this literature, analysis using STFT, RWED and PWVD might results in difficulty to achieve a good time and frequency resolution. As for CWT, it has been found that it is very reliable in analysis of bioelectrical signals in general and shows better statistical performance than other methods. Much earlier comparison study was done by Davies & Riesman [53] when they implemented the time-frequency analysis on SEMG during muscle fatigue. STFT, WVD and CWD had been chosen. In its discussion, Davies & Riesman [53] found that WVD is not a precise representation of the changing of frequency components with fatigue. STFT shows clearly the spectrum compression as muscle fatigues but CWD is said to most accurately show the frequency compression.

V. APPLICATIONS OF SEMG

A. Estimation of Muscle Fiber Conduction Velocity (MFCV)

Conduction velocity refers to the velocity in which action potential propagates through nerve fiber. In case of muscle, it is known as muscle fiber conduction velocity (MFCV). This velocity is dependent on certain properties of the fiber itself such as diameter and type.

Signal from SEMG is useful in estimating the value of MFCV. Methods for this task are either two-channel based or multi-channel based. The estimation is usually done by determining the average delay between SEMG signals recorded from two/multi points. Location of electrodes for recording is in the way that the propagation moves along the fiber between the electrodes.

Numerous literatures had report studies on MFCV using SEMG. While a number of them had interest for medical diagnosis purpose [54,55], there are lot of others only focus on the study of MFCV characteristics [56-58]. 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 [59,60], regression analysis between spatial and temporal frequencies of multiple dips introduced in the EMG power spectrum [61], using normalized peak-averaging technique [62] and minimization of the mean square error between time-filtered versions of two surface EMG signals [63].

B. Diagnosis and clinical application with new electrode design

There were several review reports regarding the reliability of SEMG technique for diagnostic purpose [64-66]. Earlier reports had argued the use of SEMG as an effective diagnostic tool especially for neuromuscular disease due to lack of literature to support the fact [64]. SEMG also had been compared to needle EMG where the former is said to be significantly inferior to the latter for neuromuscular disorder evaluation [65]. However, despite findings from such review, research on SEMG application for diagnosis of certain disease still moves on. It might be due to the non-invasive nature of the SEMG method that makes it more convincing to be used on subjects which apparently are the patients themselves.

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 [67]. However, recent development on surface electrode had brought to possibility to overcome this obstacle. A multiple surface electrode had been designed with capabilities to detect electrical activity of muscle up to single motor units [68,69]. 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 [70]. There is also high-spatial-resolution surface EMG (HSR-EMG) which uses multiple-electrode array combined with spatial filter procedure [71].

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 [72]. The result of raw signal analysis had shown significant differences between the groups. Based on outcome of this literature, the authors had urged that more studies should be initiated to explore the diagnostic value of HD-SEMG. Unfortunately, in another literature, it is reported that HD-SEMG had not been widely used as diagnostic tools in clinical neurophysiology practice [70].

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 [73], investigation on SEMG signal in carpal tunnel syndrome to observe alteration on the signal [74] and analysis of interspike interval in neuromyotonia syndrome [75].

C. Study on Parkinson Disease patient

Parkinson disease (PD) is a degenerative disease of brain which results in impairment of motor functions, impaired control of agonist muscles and speech disability. Treatment for PD, apart from medication, involves physical exercise and training to improve mobility and flexibility. Comparison of SEMG signal before and after medication or physical training on PD patient provides a useful evaluation for the effectiveness of the treatment.

Flament et al. [76] try to investigate the changes in electromyographic activity associated with the changes in movement performance in PD patients. Based on the observation on SEMG signal pattern, patients undergone physical training display fractioned, multi-burst agonist pattern, which indicates the characteristics of PD patients' SEMG recordings. However, patients' performance changed in a manner similar to that which has been observed for performance curves in neurologically normal subjects.

Earlier literature by Robichaud et al. [77] works on a similar task, but the interest is on the effect of medication. When the subjects were off medication, they lacked the ability to modulate the agonist EMG burst duration with changes in movement distance. The ability to modulate agonist EMG burst duration is characteristic of the SEMG patterns observed in healthy subjects. Medication diminished the clinical signs of Parkinson's disease, but in other way it did not restore agonist burst duration modulation with movement distance.

Other literatures that focus on PD are the use of wavelet to analyze cross-correlation time-frequency for multiple SEMG signals in Parkinson's disease [47], effect of medication by analysis on SEMG signal using wavelet approach [78], and analysis of SEMG signal morphology in PD based on histogram and crossing rate (CR) analysis. There are also works on feature extraction of SEMG signal in PD using principal component approach [79,80].

D. Biomechanics and Motion Analysis

Studies in motion or body movement are probably the area in which SEMG technique is most well suited. A simple bipolar or monopolar electrode is already sufficient for this purpose. The challenge is perhaps to deal with anomaly in signals due to noises or motion artifact. Application of SEMG in motion study is quite huge. It is possible to say that it can be used in almost all type of works concerning muscle movement, not only on limbs but also face [81,82], not limited to human but also on animals [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 include 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], just to name a few.

E. Prosthetic device

In developing prosthetic devices, researchers had make use of various type of input to the device for mean of control. Bioelectrical signals such as action potential, nerve signal, EEG, EMG or even movement of eyes retina are among the types of parameters that could be utilized for prosthetic device control. Due to the fact that prosthetic devices are often used to replace the missing part of human body, bioelectrical signal apparently fit in well to the system. Study on the use of SEMG for prosthetic device had initiated back from 1960s [89]. Until present days, numerous literatures had been produced regarding studies in this area.

Initial work on the development of EMG controlled prosthetic device would involve analysis of signal for discrimination, classification or feature extraction [90-92]. In a case of developing prosthetic device for amputees for instance, SEMG data should be acquired from subjects to analyze some SEMG signal characteristic. Data could be taken from muscles located at residual part of the limb where the prosthetic device will be attached to [7]. Remnant of muscles in residual limb might link with muscles of the lost limb. Thus, the SEMG signal obtained earlier could be analyzed and utilized for prosthetic device control so that it could imitate the movement of original limb.

The location of surface electrode on muscles for SEMG acquisition varies according to the type of prosthetic device. For prosthetic hand, extensor carpi ulnaris and flexor carpi ulnaris located on the forearm are the recommended spot for electrode placement in some literature [93,94]. In certain application, especially that engages a much complex design, more electrodes might be needed to obtain more information particularly on characteristic of different type of movement. An example of such design is prosthetic hand complete with fingers. Study by Tenore et al. [95] on decoding of individuated finger movements had used up to 32 electrodes attached on different area of forearm.

In term of SEMG feature extraction method, various techniques had been reported in literatures. There are two categories of feature extraction techniques which are time-domain feature and time-frequency domain feature. Often researchers choose to implement multiple techniques and then select the most suitable. For example, there is a work by Huang and Chiang [96] on DSP-based controller for prosthetic hand. Eight techniques for SEMG feature extraction had been used which are the integral of EMG, waveform length, variance, zero crossings, slope sign changes, Willison Amplitude, autoregressive model and cepstrum analysis. Results from all these techniques will be combined in classification stage to choose the highest classification rate before the selected feature implemented in the DSP [96]. The choice of technique to be used differs between literatures. Some literatures only interested in time-domain features. In a work on developing fingers movement of prosthetic hand for example, time-domain features performed better in real-time decoding of hand and wrist movements [97,98][95]. Another work on prosthetic hand had used both time and time-frequency domain for feature extraction and then implement the result on a neuro-fuzzy system for pattern recognition [99].

F. Speech recognition

The idea in developing an EMG based automatic speech recognition (ASR) system is based on assumption that articulatory facial muscles might contain some kind speech information [100]. 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.

Several literatures had initiated a study in this particular area. Kumar et al. [101] used artificial neural network for classification of speech based on SEMG signal. This study involves three facial muscles which are mentalis, depressor anguli oris and massetter. Manabe and Zhang [102] had implemented multi-stream Hidden Markov Model (HMM) for EMG-based speech recognition where no voice generation involve, only movement of mouth. Jia et al. [103] had worked on unvoiced digital Chinese recognition based on facial myoelectric signal. Genetic arithmetic had been used in this work for selecting the features of myoelectric signal as input of support vector machine classifier. The result from this work show that SEMG based speech recognition is a promising way towards an ASR system [103]. Another recent work from Lee [104] had also used the Hidden Markov Model to model the SEMG signal for certain Korean words.

VI. DISCUSSION

SEMG signal proved to be a useful tool for various applications concerning clinical purpose for diagnostic, sport science for performance improvement and injury detection as well as human-computer interface with regard to prosthetic device and speech recognition. Study on muscle fatigue is another well-known application of SEMG. Although there is some argument on effectiveness for use in diagnostic purpose, recent development on surface electrode design had brought to a promising future of non-invasive SEMG for clinical application.

Other than that, there are a lot of other applications of SEMG particularly for human-computer interface. As long as there is SEMG data, it could be utilized in any way. Just to list a few possible applications, SEMG could be implemented in control of robotic arm that is used for industrial purpose, to characterize hand gesture recognition [105] which might be useful in sign language, design a wheelchair based on SEMG signal [106] or develop an emotion recognition system [107]. Recently there is a project by students from Universiti Malaysia Perlis on detecting SEMG signal of drowsiness for developing a system to alert drivers [108].

However, in order to employ the SEMG, one still had to consider the effectiveness of the SEMG recording equipment that is used. For example, the number of electrodes could sometimes be crucial. To obtain details of different movement such as in prosthetic fingers, a sufficient number of electrodes had 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 on analysis technique of SEMG signal. It is essential in order to obtain features of the SEMG signal. In utilizing the SEMG as a tool, its features and characteristic is the key to provide information which then linked with the outcome of the study. Some application particularly on biomechanics and motion study had make use of statistical analysis. Features provided by SEMG obtained from numerous subjects are gathered to obtain some hypothesis according to interest of the study. Various methods of analysis are classified into amplitude, time 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.

VII. CONCLUSION

Study on SEMG is very broad, ranging from design of electrodes, recording techniques, analysis methods and application for various purposes. SEMG should be utilized especially for clinical diagnosis since its non-invasive approach makes it much more comfortable for subjects. But still there is a lot to improve especially on design of recording equipment. The design of surface electrode should be enhanced so that SEMG could be fully reliable for clinical purpose. However, for certain application especially human-computer interface, a basic requirement of recording equipment is sufficient.

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