Journal of Critical Reviews

ISSN- 2394-5125 Vol 7, Issue 12, 2020

FEATURE EXTRACTION AND CLASSIFIER IN THE DEVELOPMENT OF EXOSKELETON BASED ON EMG SIGNAL CONTROL: A REVIEW

[1]Triwiyanto Triwiyanto, [2]I Dewa Gede Hari Wisana, [3]Muhammad Ridha Mak'ruf

Department of Electromedical Engineering, Poltekkes Kemenkes Surabaya, Indonesia
Corresponding Email: triwi@poltekkesdepkes-sby.ac.id;

Received: 18.03.2020 ***Revised: 20.04.2020*** ***Accepted: 21.05.2020***

Abstract
Exoskeleton has been widely developed for the purpose of assistive and rehabilitation. This study's objective is to evaluate exoskeleton design based on EMG signal. EMG signals can provide an overview of activity in muscles, moreover the limbs motion can be represented by EMG signals through the activity. Some researchers have developed an exoskeleton by utilizing the control process through EMG signals. The selection of the right feature extraction determines the success of the classifier. Therefore, in this study, the feature extraction used in exoskeleton development research is feature extraction in the time domain (TD) MAV, RMS, IEMG, WL, SSC, and ZC. Furthermore, the classifier often used to predict the motion of the exoskeleton is an artificial neural network based on multilayer perceptron with backpropagation, neural network based on fuzzy, and support vector machines, because it has better accuracy. Some exoskeleton development for future research is discussed at the end, which includes, control system, safety, and compensation.

Keyword: EMG, Exoskeleton, Feature Extraction, Classifier

DOI: http://dx.doi.org/10.31838/jcr.07.12.155

INTRODUCTION

Increasing the number of elderly people will be followed by various problems, one of the problems faced is the weakening of the body limb function and some degenerative diseases. In order this community can carry out their social activities normally, it is necessary to have a device that can help to carry out these activities. Additionally, stroke is a disease that is the world's number-three cause of death, after a stroke, 56% of patients will experience paralysis either total paralysis or partial paralysis. In order the muscle does not decrease in muscle mass (atrophy), post-stroke patients must routinely undergo a series of therapies to restore limb function.

An exoskeleton is a metal structure mounted on the outside of an extremity that has experienced a decrease or malfunction, which aims to strengthen, increase endurance for the user and rehabilitate. Exoskeleton have been developed for many purposes for instance: prosthetic devices [1,16,25,31,32,43-46], assistive [2,3,6-9,17,19-21,39-42], and rehabilitation [4,5,10-15,18,37]. Assistive exoskeleton aims to help human body limb in motion which decreased the function. An assistive device is mounted in the human body, upper or lower limb. Additionally, a rehabilitative exoskeleton aims to help therapist and medical doctor to restore the human limb function which caused by disturbance after a post stroke or post surgery. Several researchers have developed Exoskeleton using several methods for detecting motion, including force sensors, motion sensors and EMG electrodes. EMG signals are chosen as controls in the exoskeleton because EMG signals can directly describe the activities that occur in members of body parts.

This paper aims to provide an explanation the scope of the exoskeleton based on EMG signal control in terms of the process of data acquisition, feature extraction and classifier. At the end, this paper will describe some applications of exoskeleton and future development of exoskeleton. This paper is written in several sections: the process of EMG signal acquisition, electrode layout, bio-amplifier and sampling frequency will be discussed in Section 2. Some feature extraction will be addressed in Section 3 to evaluate the characteristics of the EMG signals. In order to recognize the EMG signals then a classifier is required, this section will be discussed in Section 4. Section 5 discusses potential applications and possibilities for future development. Section 6 presents conclusions and future research.

EMG DATA ACQUISITION

EMG signal is a bio-electric signal that is generated by muscles during contractions, contractions will appear when the body limb do an activity. EMG signal is a signal that has a random and stochastic form that has frequency varies from 0 to 500 Hz, with dominant energy at frequencies between 50 and 150 Hz [2]. EMG has an amplitude of between 10 uV and 10 mV [2]. It is divided into invasive and non-invasive approaches, depending on the mechanism of the EMG signal recording. Invasive is done by using a needle electrode, which is inserted into the part of the muscle, while the noninvasive method is done by using surface electrodes, Which is placed on top of the muscle's skin to be examined. Surface electrodes can use disposable Ag (AgCl) electrodes commonly used in ECG and EEG signal recording. The latter method is more widely used in the development of exoskeleton based on EMG signal control, because it can be done by non-medical personnel or engineer. This paper will address the noninvasive use of EMG signals as a control mechanism.

Basic configuration, an exoskeleton based on EMG signal control is shown in **Figure 1**. This diagram block shows that the system is comprised of sensor, bio-amplifier, A/D converter, microcomputer system, feature extraction, classifier, driver motor, and motor.

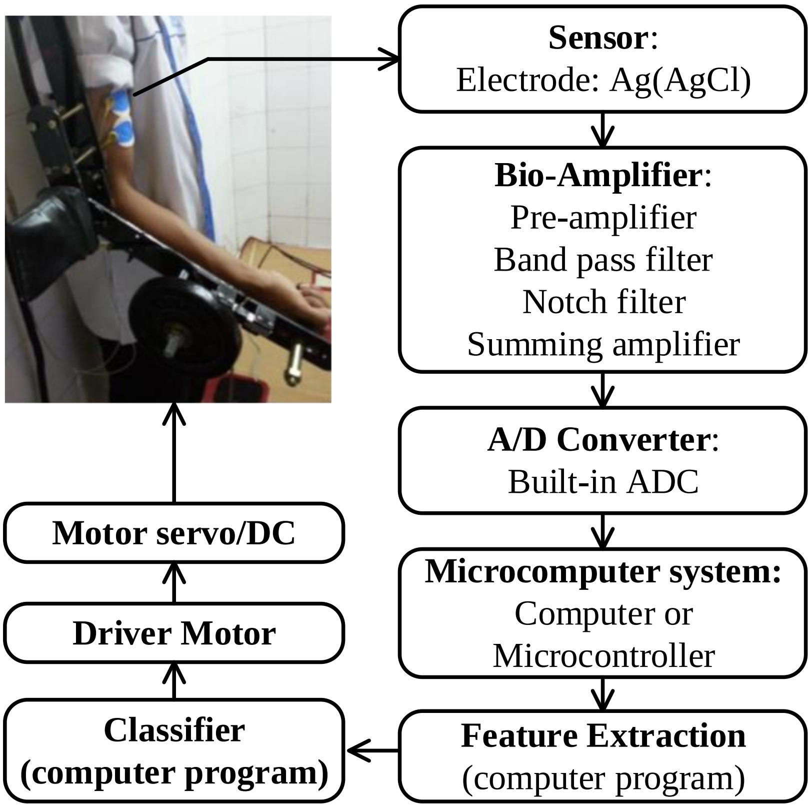

Figure 1. Exoskeleton based on EMG control

Electrode location

The electrode location is determined based on the muscle portion to be registered. Electrodes can be bipolar or monopolar [2]. The location and number of the electrode leads depends on the degree of freedom, the part of the body to be measured and the limb motion. Tang [3] placed three electrodes in three groups of muscles (anconeus, triceps brachii, biceps brachii, and brachioradialis) to detect flexion and extension motion. Lenzy [4], Song [5], Kyrylova [6] and Lalitharatne [7] built an exoskeleton on the upper limb by inserting the electrodes into the brachii biceps and brachii triceps muscles. It takes many muscles to reflect the motion in the development of an exoskeleton with greater degrees of freedom, as Rosen et. al did. [8]. They developed an exoskeleton with 2 DOF that can detect flexion, extension, pronation and supination arm movements with leads at the location of brachialis, biceps brachii, brachoradialis, and triceps Brachii. Kiguchi suggested a 3-DOF exoskeleton using biceps (lateral and medial parts), triceps (lateral and medial parts), deltoids (anterior and posterior parts), pectoral major (clavicular parts), and teres [9]. W-EXOS upper limb exoskeleton developed by Gopura detects wrist in 3 DOF movements with leads location at supinator point (SP), extensor carpi radialis brevis (ECRB), extensor carpi ulnaris (ECU), flexor carpi radialis (FCR), flexor carpi ulnaris (ECRB), extensor carpi ulnaris (ECU), flexor carpi radialis (FCR), flexor carpi ulnaris (SPR) FCU) and pronator teres (PT)[10]. Exoskeleton developed by Artemiadis [11], and Loconsole [12] detect the shoulder and elbow motion through deltoid (anterior), deltoid (posterior), deltoid (middle), pectoralis major, biceps brachii, brachioradialis, triceps brachii muscles.

Bio-amplifier

EMG signals have a small amplitude with a range of 0.01 mV to 10 mV [2], in order this signal can be processed by a computer system or microcontroller, it requires a pre amplifier to strengthen the signal. Bio-amplifier generally consists of 4 parts: preamplifier, bandpass filter, notch filter and summing amplifier. Preamplifier is the main part of the bio-amplifier circuit, which serves to strengthen the EMG signal and reduce common mode noise, if there are two differential inputs from the preamp. Bandpass filter functions to pass EMG signals according to the spectrum characteristics of EMG signals that reach frequencies from 0 to 500 Hz [2]. The noise generated by the power line is the biggest noise that interfere the bio-amplifier circuit, therefore the notch filter 50 Hz circuit is a solution to reduce the noise. An EMG signal is an oscillating signal resembling the form of an ac signal, so that it can be processed by the ADC then a summing amplifier is needed to increase the signal level to the direct current (DC) form. Several companies have made bio-amplifiers for the purposes of EMG signal data acquisition, completed with several channels. Bio-amplifier can also be made with custom as desired, generally using the AD620 or INA121 instrumentation amplifier.

Research conducted by Fleischer used electrodes with built-in amplifiers (Delsys, Inc. Boston, USA) [13], With a 1000 V / V gain and a 20 and 450 Hz bandpass filter. Loconsole [12] using g.USBAmp Amplifier amplifier for data acquisition which collected five channel of EMG signal. Rosen used an EMG amplifier (BIOPAC-EMG100A) with a gain of 2000-5000 V / V, depending on the subject to be measured. The measurements of EMG signal was located at the biceps and triceps points [8]. To strengthen the EMG signal, Lalitharatne uses an amplifier [MEG-6108, Nihon Koden Co.] [14] in the development of exoskeleton based on EMG signal control.

Several researchers used a home made bio-amplifier to process EMG signals, Ramos designed an INA126P instrumentation amplifier with a gain of 805 V / V and a 16-bit analog input card data acquisition of NI 9205 [15]. The embedded device implemented in artificial leg by Lin used the instrumentation amplifier AD620, which processes EMG signals in the frequency range of 10-500 Hz, with a maximum gain of 100,000 V / V in accordance with the EMG signal input range of around 50uV-10 mV, to achieve 0- 5V [16]. The MC68HC11A8 microcontroller based prothetic system built by Patel used a differential amplifier with a gain of 20,000 V / V. Additionally, 10-3000 Hz bandpass filter was applied on the EMG signals which collected from bicep, triceps, quadratus pronator, and supinator muscles [17]. An aided ARM robot training developed by Song used a custom-made bio-amplifier that uses instrumentation amplifiers (INA126, Texas Instruments, Dallas, TX) with 1000 V / V gain and 10-400 Hz bandpass filter [18].

Frequency sampling

In EMG signals recording which using an analog to digital converter, frequency sampling must meet Nyquist rules, which is a minimum of two time of maximum frequency. In the data acquisition, the sampling frequency is done on the microcontroller or computer system using the timer function. Frequency sampling is set based on the highest frequency of the measured EMG signal. Gopura [19] applied a frequency sampling of 2 kHz to record EMG signal in sixteen lead. On a PCI 6036E DAQ (data acquisition) card, National Instruments, Austin, TX, Song applied a 1000 Hz frequency sampling connected to a device for EMG signal recording [18]. Kyrylova [6] used a frequency sampling of 1000 Hz based on Biosignalsplux (Plux) to measure the EMG signal on biceps dan triceps. Lalitharatne [14] used a 2000 Hz sampling frequency to collect the sinyal EMG for the elbow dan shoulder angle measurement. Andreasen [20] used a frequency sampling of 1000 Hz to measure the EMG signal on biceps.

FEATURE EXTRACTION

Due to a large amount of data collection EMG signals can not be analyzed directly for classification purposes in the TD series. A large number of data representing the EMG signal requires a feature extraction process. The feature extraction process that is often developed for the purposes of EMG signal analysis is in the TD, frequency and wavelet (time-frequency) domains.

TD Features

Feature extraction in the TD has advantages in terms of time-consuming data processing and simple equations. Therefore, some studies on exoskeleton preferred to use TD feature extraction. The extraction method for the function is essentially shown in Figure 2. The extraction process sequentially comprises the EMG signal raw, the windowing technique (adjacent or overlap) [21] [22], and the EMG feature (time, frequency or time-frequency) [23][24].

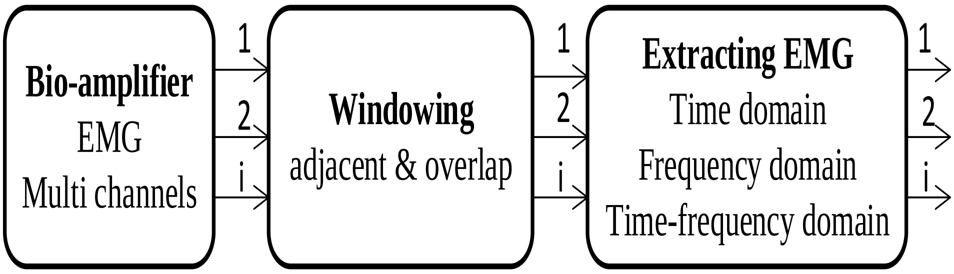

Figure 2. Feature extraction process

Several features extraction in the TD that are often used in exoskeleton research are as follows. Mean absolute value (MAV) is a method used for the extraction of EMG signals. In the development of exoskeletons, Kiguchi [9], Andreasen [20] and Loconsole [12] used MAV as the classifier data. The MAV equation is shown as follow (1):

$$MAV = \frac{1}{N}\sum_{i=1}^{N} | x_i | \quad (1)$$

Root mean square (RMS) is one of the features used very frequently in many advancements of exoskeletons. Some research on exoskeleton uses this feature for signal extraction EMG [3], [25], [10], [7], [26], [27], [28], [1]. With the following mathematical equation, this feature is identical to the standard deviation system (2).

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (2)$$

Integrated EMG reflects the total number of EMG signals in some windows. This feature is usually used to detect whether an EMG signal is in a contraction state. Some exoskeleton studies use this feature for the extraction of EMG signals [4], [28]. Integrated EMG is expressed in mathematical equations as follows (3):

$$IEMG = \sum_{i=1}^{N} | x_i | \quad (3)$$

For calculating the complexity of EMG signals, waveform length (WL) is used. WL is the accumulated length of EMG signals in the measured segments. Some exoskeleton researchers use WL as an extraction feature [8], [25], [29]. Ding uses the WL feature to find out the elbow joint movement [30]. Liu uses this feature in the development of multifunctional prostheses [31]. The WL equation is shown in following equation (4):

$$WL = \sum_{i=1}^{N-1} | x_{i+1} - x_i | \quad (4)$$

Sign Slope Change (SSC) is a feature frequently used to get EMG signal frequency information. SSC indicates the number of slopes in sign form. The threshold is used for the noise reduction behind the EMG signal. Some studies of exoskeletons use this method to obtain the EMG features [32], [1] (5).

$$SSC = \sum_{i=1}^{N-1} [\, f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$$

$$f(x) = \begin{cases} 1, if \rightarrow x \geq threshold \\ 0, otherwise \end{cases} \quad (5)$$

Zero Crossing (ZC) is a method for viewing information on the signal frequency without using the transformation step. ZC is determined according to the number of signals that cross the zero point. When ZC feature was applied, the noise behind the EMG signal does not count. Additionally, a threshold is needed as a minimum amplitude limit. Chan uses the ZC function as one of the features in the Fuzzy rule, in the creation of protheses [1]. The mathematical equation for the ZC feature is as follows (6):

$$ZC = \sum_{i=1}^{N-1} [\, f\,(x_i \times x_{i+1}) \cap |\, x_i - x_{i+1}\,| \geq threshold$$

$$f\,(x) = \begin{cases} 1, if \;\rightarrow x \geq threshold \\ 0, otherwise \end{cases}$$

(6)

where x_i is the EMG signal on the-*i, N* assign the length of the EMG signal and *threshold* is to limit the amplitudo level of signal.

Frequency Domain

Frequency domain analysis essentially uses the Fast Fourier Transform method [33][34], That converts the TD signal to the frequency domain, so that the EMG signal spectrum band will be known to be processed. The EMG signal analysis, also used for the assessment of isometric fatigue, is a frequency domain analysis. The frequency domain characteristics often used are mean frequency (MNF), mean power frequency (MPF) and median frequency (MDF). The EMG signal spectrum will undergo a change in isometric fatigue determination, with the MDF location decreasing. In the study of exoskeleton based on frequency domain, it is almost no one uses this domain, because it requires a process of transformation from the TD to frequency, so it is less precise when used for real time control purposes.

MDF is a median frequency where the EMG power spectrum is split into two regions of equal amplitude. It is divided into two regions due to being half the total power. As explained below, it is measured in two stages: First, the signal strength in the entire spectrum is summed up, and divided by two. A frequency at which combined intensity (i.e. all intense) is selected in the second stage. The MDF equation is shown in following equation (7):

$$MDF = \frac{1}{2} \sum_{j=MDF}^{M} P_j$$

(7)

where, Pj shows the EMG power range at frequencies j and M shows the frequency length.

The MNF value is the product of spectrum frequency and amplitude and is equal to the spectrum sum of all these products as shown in equation (8). This feature is written as follow (8):

$$MNF = \frac{\sum_{j=1}^{M} f_j P_j}{\sum_{j=1}^{M} P_j}$$

(8)

Where fj describes the EMG power spectrum frequency value at frequency j, Pj indicates the EMG power spectrum at frequency j and the frequency spectrum length M.

MNP is an EMG frequency spectrum mean frequency. It is definable as follows (9):

$$MNP = \frac{\sum_{j=1}^{M} P_j}{M}$$

(9)

Where, Pj shows the frequency length (M) of the EMG power spectrum at frequencies j.

Time-Frequency Domain

The Fast Fourier Transform (FFT) method decompose only signals in the TD into frequency components, but this FFT method cannot determine the frequency location at a particular time. One way to solve this is to use the wavelet method. Wavelet method is widely used for the purposes of EMG signal analysis to determine the position of the motion and fatigue state of the muscles [23][35] but is not used for the exoskeleton control process. The material related to time-frequency domain can be obtain in some references.

CLASSIFIER

The output of the EMG feature was not able to define the EMG signal pattern following its motion; therefore, a classification process based on the input of the EMG feature is required. Additionally, some parameters that are often encountered during the classification process related to the characteristics of the EMG signal are, electrode position, sweat and fatigue. These parameters can increase the classification error, so that those issues must be taken into account in future work. Some exoskeleton studies use modeling with pattern recognition in the classifier to estimate the joint angle of the exoskeleton [3] [12] [36] [27]. The development of exoskeleton by using modeling based on classifier has weaknesses in terms of complexity in the learning process and considerable time consumption. Some other researchers who develop an exoskeleton, without using a classifier, are using the Hill Based method [7,26,41] and based on the 2nd order low pass filter EMG signal model [4]. Generally, a standard machine learning was shown in **Figure 3** which consisted of EMG features, machine learning, output, and decoder.

Artificial Neural Network

Classifier often used to recognize exoskeleton motion patterns is the MLP artificial neural network (ANN) using the backpropagation method in learning process. Tang [3] uses a back propagation neural network classifier, with 4 input nodes, the hidden nodes are trial and error with consideration that they are not too big and not too small because it will affect the error of the classifier and the speed of the learning process. The ANN performance in modeling the EMG signal to the exoskeleton angle obtained a high correlation value (R^2) of 0.87. The sigmoid transfer function that can be used for ANN learning is as follows:

$$y = f(\sum w_i x_i) = \frac{1}{1+ e^{-(\sum w_i x_i)}}$$

(7)

where y indicates the output, x_i shows the input, w_i defines the weight factor for the input, hidden and output layer, e is the exponential function dan $f()$ is sigmoid transfer function.

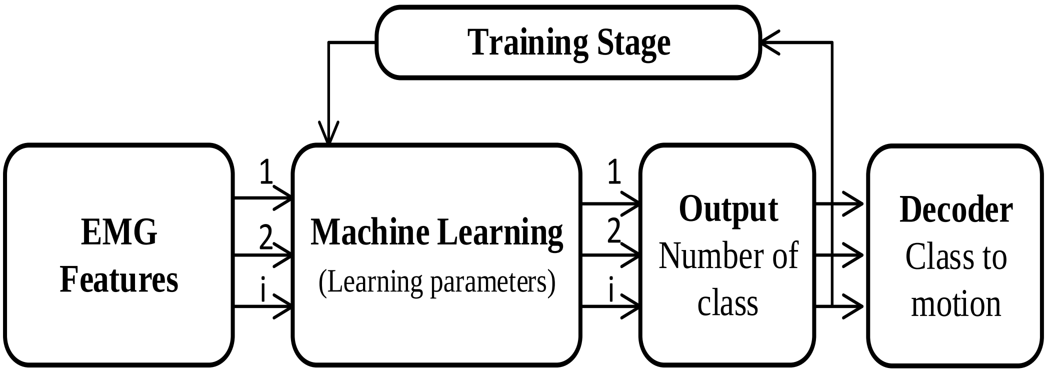

Figure 3. Standar machine learning procedures

Lonconsole [12] built the Time Delay ANN to predict shoulder and elbow joint angles on the exoskeleton for rehabilitation. The results of the evaluation of the application of ANN time delay obtained RMSE performance value = 1.19. Lee [36]used ANN time delay to predict knee joint in identifying seated to standing movements, with an RMSE value = 0.02234. ANN-based radials are one of the ANN methods in the learning process on the network using Gaussian equations. Wang [27] used radial NN basis to predict elbow joint, with the best performance obtained RMSE = 0.063. Several researchers developed ANN to predict joints in the upper limb based on EMG signal based on various TD feature [27], [28], [30-39].

Fuzzy

Fuzzy logic is a method that used for the purposes of classifying EMG signals into several classes. Furthermore, fuzzy logic can also be used for control of the exoskeleton. Research conducted by Taslim, a fuzzy controller was built to detect the movements from sitting to standing in the lower limb knee [38]. Gopura developed an exoskeleton with three DOF motion through EMG signals with classification using fuzzy rule controller [19].

Neuro Fuzzy

Neuro Fuzzy (NF) is a hybrid of neural networks and fuzzy logic, so it is expected that with this algorithm a system that has the ability to learn like humans and has the ability to make logical decisions. Neuro fuzzy algorithm is also widely applied to the exoskeleton by using the extraction of EMG signal features as input. Using the Neuro Fuzzy algorithm, Kiguchi developed the upper limb exoskeleton with 4 DOF motions, 3 DOF on the shoulders and 1 DOF on the elbow [9]. Upper limb human assist developed by Gopura is used to control 3 DOF movements based on neuro fuzzy control [10]. Neuro fuzzy algorithm, in addition to the control needs of the exoskeleton, can also be modified in the network weights so that it can be used as a compensator for other parameters, as developed by Lalitharatne [39]. When a muscle fatigue occurs, the EMG signal will change both in amplitude and frequency. Additionally, the median frequency will be shift to the lower frequency. This phenomenon can be used to compensate for the neuro fuzzy weights during the control process.

SVM

Support Vector Machines (SVM) are techniques for classification that optimize margins between classes. Khokhar [25] uses the SVM method to recognize 13 classes of movement on the wrist exoskeleton, with the highest accuracy of 99.47%. SVM effectiveness testing was also carried out by Yoshikawa [40] for the prediction of joint angles on the robot hand, with the highest accuracy of 95.7%. Several other researchers [43-46] used the SVM method for the classification process of movement.

POTENSIAL APPLICATION

Studies related to the exoskeleton have been developing in the past 15 years, along with the needs in the community. Various exoskeleton models have been developed, starting from the simplest exoskeleton model with an ON-OFF control system, non pattern recognition to the exoskeleton with embedded pattern recognition [42] [43]. From the results of the review paper, this still shows that there are still a number of possible applications of exoskeleton associated with control, safety and compensation systems. The development of the exoskeleton is still wide open for further research, especially the exoskeleton for post-stroke or post-operative therapy needs. In some previous studies the subjects tested were generally using humans in a healthy or normal condition, in subsequent studies it would be better if the trials were carried out in post-stroke patients. The exoskeleton is expected to be able to respond and follow movements according to human intention so that in subsequent studies it is expected to improve the control system algorithm so that the exoskeleton can follow the speed and acceleration of the user. This can be added gyroscope sensor and accelerometer.

The focus of the area that some previous researchers worked on was the development of control systems and the recognition of EMG signal patterns. Safety is one thing that is very important in every use of instrumentation equipment, especially those related to patients directly, so that the development of the exoskeleton is expected to be able to ensure patient safety in the event of a malfunction. One of the sensors that can be used directly for safety purposes is by utilizing EOG (electrooculography) signals through electrode leads. So that in patients after stroke still have the ability to move the eyeball for the purpose of stopping the operation of the exoskeleton, if the patient feels uncomfortable.

EMG signals have very complex characteristics and depend on several parameters, changes in these parameters will affect the characteristics of the amplitude and frequency. These parameters include, position shift, change in distance and orientation of the electrode from its original position. Sweat is an element consisting of salt which can also affect the resistance of the skin, so that it will cause resistance between the electrodes to change which can impact the characteristic EMG signal amplitude. Long use of exoskeleton can induce patient's tiredness. Some previous researchers reported that fatigue would affect EMG signal characteristics. The amplitude will increase and the frequency will decrease [44] [45]. These parameters are still wide open for exploration on the development of the exoskeleton.

CONCLUSION

EMG signals are bio-electric that are generated by muscles when they do muscle contraction. Through spinal cord neural system, the brain instructs the limbs to do a motion. EMG signals carry a lot of information related to limb movements. The use of EMG signals for control purposes is very affective because it will reflect human intention. Feature extraction in the TD is preferred by some researchers because it is an uncomplicated algorithm and less computational time. Therefore, in order to control exoskeleton in real time, it can work better. EMG signal modeling for estimation of the exoskeleton angle can be done by several methods, one method that is often used is to use the ANN classifier and Fuzzy NN.

Research that can be developed in the future is related to natural control, safety and compensation. There are many physical parameters on muscle need to address in developing a compensation method for instance muscle fatigue, sweat and artifact noise.

REFERENCE

1. F. H. Y. Chan, Y. S. Yang, F. K. Lam, Y. T. Zhang, and P. a. Parker, "Fuzzy EMG classification for prosthesis control," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 3, pp. 305–311, 2000.
2. C. J. De Luca, "Surface Electromyography : Detection and Recording," *DelSys Inc.*, vol. 10, no. 2, pp. 1–10, 2002.
3. Z. Tang, K. Zhang, S. Sun, Z. Gao, L. Zhang, and Z. Yang, "An Upper-Limb Power-Assist Exoskeleton Using Proportional Myoelectric Control," *Sensors*, vol. 14, no. 4, pp. 6677–6694, Apr. 2014.
4. T. Lenzi, S. M. M. De Rossi, N. Vitiello, and M. C. Carrozza, "Intention-Based EMG Control for Powered Exoskeletons," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 8, pp. 2180–2190, Aug. 2012.
5. R. Song, K. Y. Tong, X. Hu, and L. Li, "Assistive control system using continuous myoelectric signal in robot-aided arm training for patients after stroke," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 4, pp. 371–379, 2008.
6. A. Kyrylova, T. Desplenter, A. Escoto, S. Chinchalkar, and a L. Trejos, "Simplified EMG-driven Model for Active-Assisted Therapy *," *IROS 2014 Work. Rehabil. Assist. Robot. Bridg. Gap Between Clin. Robot.*, p. 6, 2014.
7. T. D. Lalitharatne, K. Teramoto, Y. Hayashi, T. Nanayakkara, and K. Kiguchi, "Evaluation of Fuzzy-Neuro Modifiers for Compensation of the Effects of Muscle Fatigue on EMG-Based Control to be Used in Upper-Limb Power-Assist Exoskeletons," *J. Adv. Mech. Des. Syst. Manuf.*, vol. 7, no. 4, pp. 736–751, 2013.
8. J. Rosen, M. Brand, M. B. Fuchs, and M. Arcan, "A myosignal-based powered exoskeleton system," *IEEE Trans. Syst. Man, Cybern. Part ASystems Humans.*, vol. 31, no. 3, pp. 210–222, 2001.
9. K. Kiguchi, T. Tanaka, and T. Fukuda, "Neuro-fuzzy control of a robotic exoskeleton with EMG signals," *IEEE Trans. Fuzzy Syst.*, vol. 12, no. 4, pp. 481–490, 2004.
10. R. a R. C. Gopura and K. Kiguchi, "Electromyography (EMG)-signal based fuzzy-neuro control of a 3 degrees of freedom (3DOF) exoskeleton robot for human upper-limb motion assist," *J. Natl. Sci. Found. Sri Lanka*, vol. 37, no. 4, pp. 241–248, 2009.
11. P. K. Artemiadis and K. J. Kyriakopoulos, "EMG-Based Position and Force Estimates in Coupled Human-Robot Systems: Towards EMG-Controlled Exoskeletons," in *Springer Tracts in Advanced Robotics*, vol. 54, 2009, pp. 241–250.
12. C. Loconsole, S. Dettori, A. Frisoli, C. A. Avizzano, and M. Bergamasco, "An EMG-based approach for on-line predicted torque control in robotic-assisted rehabilitation," *2014 IEEE Haptics Symp.*, pp. 181–186, 2014.
13. C. Fleischer, A. Wege, K. Kondak, and G. Hommel, "Application of EMG signals for controlling exoskeleton robots," *Biomed. Tech.*, vol. 51, no. 5–6, pp. 314–319, 2006.
14. T. D. Lalitharatne, Y. Hayashi, K. Teramoto, and K. Kiguchi, "A study on effects of muscle fatigue on EMG-based control for human upper-limb power-assist," in *2012 IEEE 6th International Conference on Information and Automation for Sustainability*, 2012, pp. 124–128.
15. J. L. a S. Ramos and M. a Meggiolaro, "Use of surface electromyography for human amplification using an exoskeleton driven by artificial pneumatic muscles," in *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, 2014, pp. 585–590.
16. A. Lin, X. Zhang, H. Huang, and Q. Yang, "Design and implementation of an embedded system for neural-controlled artificial legs," *2010 IEEE Work. Heal. Care Manag. WHCM 2010*, pp. 1–6, 2010.
17. P. Patel, S. Allen, and G. Rapach, "Microcontroller based prosthetic device using myoelectric signal," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1988, pp. 1427–1428 vol.3.
18. R. Song, K. Y. Tong, X. Hu, and L. Li, "Assistive control system using continuous myoelectric signal in robot-aided arm training for patients after stroke," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 4, pp. 371–379, 2008.
19. R. A. R. C. Gopura and K. Kiguchi, "Application of Surface Electromyographic Signals to Control Exoskeleton Robots," in *Applications of EMG in Clinical and Sports Medicine*, InTech, 2012.
20. D. S. Andreasen, S. K. Allen, and D. a. Backus, "Exoskeleton with EMG based active assistance for rehabilitation," *Proc. 2005 IEEE 9th Int. Conf. Rehabil. Robot.*, vol. 2005, pp. 333–336, 2005.
21. T. Triwiyanto, O. Wahyunggoro, and H. Nugroho, Hanung Adi, Herianto, "Performance Analysis of the Windowing Technique on Elbow Joint Angle Estimation Using Electromyography Signal Performance Analysis of the Windowing Technique on Elbow Joint Angle Estimation Using Electromyography Signal," in *Journal of Physics: Conference Series*, 2018, vol. 1108, pp. 1–6.
22. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and Herianto, "Effect of window length on performance of the elbow-joint angle prediction based on electromyography," in *Journal of Physics: Conference Series*, 2017, vol. 853, p. 012014.
23. T. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and H. Herianto, "Continuous wavelet transform analysis of surface electromyography for muscle fatigue assessment on the elbow joint motion," *Adv. Electr. Electron. Eng.*, vol. 15, no. 3, pp. 424–434, 2017.
24. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and Herianto, "An investigation into time domain features of surface electromyography to estimate the elbow joint angle," *Adv. Electr. Electron. Eng.*, vol. 15, no. 3, pp. 448–458, 2017.
25. Z. O. Khokhar, Z. G. Xiao, and C. Menon, "Surface EMG pattern recognition for real-time control of a wrist exoskeleton.," *Biomed. Eng. Online*, vol. 9, p. 41, 2010.
26. K. Kiguchi and Q. Quan, "Muscle-model-oriented EMG-based control of an upper-limb power-assist exoskeleton with a neuro-fuzzy modifier," *IEEE Int. Conf. Fuzzy Syst.*, pp. 1179–1184, 2008.
27. S. Wang, Y. Gao, J. Zhao, T. Yang, and Y. Zhu, "Prediction of sEMG-based tremor joint angle using the RBF neural network," *2012 IEEE Int. Conf. Mechatronics Autom. ICMA 2012*, pp. 2103–2108, 2012.
28. K. Kiguchi and Y. Hayashi, "Estimation of joint torque for a myoelectric arm by genetic programming based on EMG signals," *World Autom. Congr. (WAC), 2012*, pp. 1–4, 2012.
29. X. Guo, P. Yang, L. Chen, X. Wang, and L. Li, "Study of the control mechanism of robot-prosthesis based-on the EMG processed," *Proc. World Congr. Intell. Control Autom.*, vol. 2, pp. 9490–9493, 2006.
30. Q. Ding, X. Zhao, A. Xiong, and J. Han, "A Novel Motion Estimate Method of Human Joint with EMG-Driven Model," in *2011 5th International Conference on Bioinformatics and Biomedical Engineering*, 2011, no. 1, pp. 1–5.
31. X. Liu, R. Zhou, L. Yang, and G. Li, "Performance of various EMG features in identifying arm movements for control of multifunctional prostheses," *Proc. - 2009 IEEE Youth Conf. Information, Comput. Telecommun. YC-ICT2009*, pp. 287–290, 2009.
32. M. R. Ahsan, M. I. Ibrahimy, and O. O. Khalifa, "EMG motion pattern classification through design and optimization of Neural Network," *2012 Int. Conf. Biomed. Eng.*, no. February, pp. 175–179, 2012.
33. A. Luttmann, M. Jager, J. Sökeland, and W. Laurig, "Electromyographical study on surgeons in urology. II. Determination of muscular fatigue," *Ergonomics*, vol. 39, no. 2, pp. 298–313, 1996.
34. S. K. Chowdhury and A. D. Nimbarte, "Comparison of Fourier and wavelet analysis for fatigue assessment

during repetitive dynamic exertion," *J. Electromyogr. Kinesiol.*, vol. 25, no. 2, pp. 205–13, 2015.
35. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and H. Herianto, "DWT analysis of sEMG for muscle fatigue assessment of dynamic motion flexion-extension of elbow joint," in *Proceedings of 2016 8th International Conference on Information Technology and Electrical Engineering: Empowering Technology for Better Future, ICITEE 2016*, 2017.
36. J. K. Lee and Y. Nam, "Knee joint moment estimation using neural network system identification in sit-to-stand movement," *2008 Int. Conf. Control. Autom. Syst.*, pp. 544–547, 2008.
37. D. Li and Y. Zhang, "Artificial Neural Network Prediction of Angle Based on Surface Electromyography," *2011 Int. Conf. Control. Autom. Syst. Eng.*, pp. 1–3, 2011.
38. S. M. Taslim Reza, N. Ahmad, I. A. Choudhury, and R. A. R. Ghazilla, "A study on muscle activities through surface EMG for lower limb exoskeleton controller," in *2013 IEEE Conference on Systems, Process & Control (ICSPC)*, 2013, pp. 159–163.
39. T. D. Lalitharatne, Y. Hayashi, K. Teramoto, and K. Kiguchi, "Compensation of the effects of muscle fatigue on EMG-based control using fuzzy rules based scheme.," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2013, pp. 6949–52, 2013.
40. M. Yoshikawa, M. Mikawa, and K. Tanaka, "A myoelectric interface for robotic hand control using support vector machine," *2007 IEEE/RSJ Int. Conf. Intell. Robot. Syst.*, pp. 2723–2728, 2007.
41. S. Bitzer and P. Van Der Smagt, "Learning EMG control of a robotic hand: Towards Active Prostheses," *Proc. - IEEE Int. Conf. Robot. Autom.*, vol. 2006, no. May, pp. 2819–2823, 2006.
42. T. Triwiyanto, I. P. A. Pawana, B. G. Irianto, T. B. Indrato, and I. D. G. H. Wisana, "Embedded system for upper-limb exoskeleton based on electromyography control," *Telkomnika (Telecommunication Comput. Electron. Control.*, vol. 17, no. 6, pp. 2992–3002, 2019.
43. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and Herianto, "String actuated upper limb exoskeleton based on surface electromyography control," *Proc. - 2016 6th Int. Annu. Eng. Semin. Ina. 2016*, pp. 176–181, 2017.
44. Triwiyanto, O. Wahyunggoro, H. Adi Nugroho, and Herianto, "Continuous wavelet transform analysis of surface electromyography for muscle fatigue assessment on the elbow joint motion," *Adv. Electr. Electron. Eng.*, vol. 15, no. 3, 2017.
45. T. Triwiyanto, O. Wahyunggoro, H. A. Nugroho, and H. Herianto, "Muscle fatigue compensation of the electromyography signal for elbow joint angle estimation using adaptive feature," *Comput. Electr. Eng.*, vol. 71, no. July, pp. 284–293, Oct. 2018.