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Trends and Challenges in EMG Based Control Scheme of Exoskeleton Robots- A Review

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Abstract—In the present review article the application of robotics in the medical field has been explored. Exoskeleton robots are being used in rehabilitation, extending the strength of humans and substituting for lost limbs. Present focus of research is in the area of active powered exoskeleton robots especially surface electromyogram (sEMG) controlled ones. We restrict our discussion to sEMG based control scheme only as EMG signals provide rich motor control information from which the user's intention can be detected, thereby making EMG the most suited approach for designing exoskeleton robots. Usually exoskeleton robots are worn by patients with disabilities; hence their control should be as efficient as possible so as to closely mimic natural human motion. This consideration makes the implementation of sEMG exoskeleton robots very challenging. We review the various sEMG based control schemes which are presently employed in designing exoskeleton robots and discuss the challenges faced in these schemes.

Index Terms—Active powered exoskeletons, Exoskeleton robots, sEMG control.

I. Introduction

Exoskeletons are wearable robots (WR) exhibiting a close cognitive and physical interaction with the human user. These are rigid robotic exoskeletal structures that typically operate alongside human limbs [1]. A robotic exoskeleton system (or an exoskeleton robot) is a novel man-machine intelligent system. It fully merges the human intelligence and machine power [2]. The robotic exoskeleton transmits torques to the human joints from the actuators through its links [2]. The robotic exoskeleton technology has acquired a rapid development in recent years with the advances in the technology in Mechanical engineering, Biomedical engineering, Electronics engineering & artificial intelligence [2].

Various design issues in Exoskeleton robotics include:

- Mechanical design
- Issues in designing control scheme to achieve more natural control
- Safety etc.

Mechanical design issues include the limitation of actuator technology present today, complexity of human joints, and materials used for Exoskeleton robots.

The second design issue is the control of exoskeleton robots. Although, several research prospects have been taken up in order to control the exoskeleton robots using Myoelectric (EMG) signal, still very few real time myoelectric signal controlled exoskeleton robots are available in the market today.

The third and very important issue with exoskeleton robots is the safety issue. Exoskeleton being WR, are worn by patients, which affects the human body directly. They therefore must be safe enough and should not restrict the function of other body parts. That is why the human-Robot Interaction (HRI) becomes very important while designing the Exoskeleton robots. There are two parts of HRI. One is the physical human-robot interaction (pHRI) which is related to the physical contact between human object and robot for transferring the power from exoskeleton robots to the human or vice-versa. Second is the cognitive human-robot interaction (cHRI) related to relaying the information from human object to exoskeleton robots or vice-versa [3].

II. TRENDS IN EMG BASED CONTROL SCHEME OF EXOSKELETON ROBOTS

There are various trends in exoskeleton robots like increasing miniaturization, compactness and integration of hybrid etc. The scope of this paper is restricted to review the current trends in myoelectric signal control scheme of exoskeleton robots.

Zeeshan O Khokhar et al in [4] presented the use of pattern recognition of EMG signal for estimating the torque applied by a human wrist and its real-time implementation to control a novel two degree of freedom wrist exoskeleton prototype (WEP).

Michał A. Mikulski in [5] proposed control algorithms for Single-DOF Powered Exoskeleton used in the process of physiotherapy and rehabilitation of the human upper limb. Proposed algorithms use EMG signals from single muscles as well as antagonist muscle pairs, to maximize the user's intuitive control over the exoskeleton system.

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H.He and K.Kiguchi in [6] proposed an electromyogram (EMG) based control (i.e., control based on the skin surface EMG signals of the user) for the exoskeleton robot to assist physically weak person's lower-limb motions. The skin surface EMG signals are mainly used as the input information for the controller.

Zhang Zhen et al in [7] presented a paper concerned with a control method of an exoskeletal ankle based on surface electromyographic (SEMG) signals. The SEMG signals are acquired, and sent to the computer. The computer deals with the SEMG signals and generates the control orders. The control orders are passed to the motor controller which drives the exoskeleton to move.

Zhang Zhen et al in [8] presented an article studying human ankle movement based on surface electromyographic (SEMG) signals. Four types of movement were designed including maximum voluntary contraction, bending/extending, going down, and walking.

P. Geethanjali et al in [9] developed a four-channel EMG signal acquisition system as part of an on-going research in the development of an active prosthetic device. The acquired signals have been used for identification and classification of six unique movements of hand and wrist, viz. hand open, hand close, wrist flexion, wrist extension, ulnar deviation and radial deviation.

Sang Wook Lee and Kristin M. Wilson et al in [10] developed a robust subject-specific electromyography (EMG) pattern classification technique to discriminate between the intended manual tasks from muscle activation patterns of stroke survivors. This study demonstrated the feasibility of the EMG pattern classification technique to discern the intent of stroke survivors.

Feng Zhang et al in [11] extracted a new feature of surface electromyography (SEMG) by using discrete wavelet transform (DWT) which is proposed for motion recognition of upper limbs, and this method can be eventually used for rehabilitation robot control. Seven traditional features of SEMG have also been extracted for comparative study. They are integral of absolute value (IAV), difference absolute mean value (DAMV), zero crossing (ZC), variance (VAR), mean power spectral density (MPSD), mean frequency (MF) and median frequency (MDF) respectively.

Jose M. Ochoa et al in [12] have developed an instrument, termed the J Glove, to provide active assistance of digit extension to facilitate practice of grasp-and-release tasks. The device monitors EMG signals, both for ensuring active participation of the user and for providing feedback of EMG patterns to the user.

N.S.K. Ho et al in [13] designed an exoskeleton hand robotic training device which is especially for persons after stroke to provide training on their impaired hand by using an exoskeleton robotic hand. This is actively driven by their own muscle signals. It detects the stroke person’s intention using his/her EMG signals from the hemiplegic side and assists in hand opening or hand closing functional tasks.

Rhonira Latif et al in [14] described a new approach for classification of EMG of the flexion and extension signals. Multivariate Autoregressive (MVAR) model has been applied to a two-channel set of EMG signals from the bicep and tricep muscles during flexion and extension positions of the elbow. The MVAR coefficients are then used to define the Directed Transfer Function (DTF), which estimates the strength of the direction of the signals flow between the channels. The maximum strength of the DTF was used as the frequency domain features (training data) for EMG classification via support vector machine (SVM) algorithm. The overall method described here has a potential to detect and classify the type and level of muscular disorder from the way the muscle signals interact with each other.

Xiao Hu, Ping Yu et al in [15] introduced a novel and simple method of extracting the general features of two surface EMG signal patterns: forearm supination (FS) and forearm pronation (FP) surface EMG signals. The surface EMG signal was divided into two segments appropriately at the preparation stage and the action stage. Relative wavelet packet energy (RWPE), symbolized by p_{np} and p_{na} respectively at the preparation stage and the action stage, where n denotes the nth frequency band (FB). The surface EMG signal was firstly calculated, and then the change (P_n=p_{na}-p_{np}) was determined.

Jacob Rosen et al in [16] presented the scope of the integration of a human arm with a powered exoskeleton (orthotic device) and its experimental implementation in an elbow joint, naturally controlled by the human. The Human–Machine interface was set at the neuro-muscular level, by using the neuro-muscular signal (EMG) as the primary command signal for the exoskeleton system. The EMG signal along with the joint kinematics were fed to a myoprocessor (Hill-based muscle model) which in turn predicted the muscle moments on the elbow joint.

Ben H. Jansen et al in [17] presented a method to quantify the intricate (to involve) phasing and activation levels of a group of muscles during gait (manner of walking or running). The core of their method was the multidimensional representation of the EMG activity observed during a single stride. The representation was referred to as a “trajectory.” A hierarchical clustering procedure has been used to identify representative classes of muscle activity patterns. The relative frequencies with which these motor patterns occur during a session (i.e., a series of consecutive strides) were expressed as histograms. Changes in walking strategy have been reflected as changes in the relative frequency with which specific gait patterns occurred.

Kazuo Kiguchi et al in [18] proposed a robotic exoskeleton for human upper-limb motion assist, a hierarchical neuro-fuzzy controller for the robotic exoskeleton, and its adaptation method. The robotic exoskeleton is controlled basically based on the electromyogram (EMG) signals, since the EMG signals of human muscles are important signals to understand how the user intends to move.

Satoshi Kawai et al in [19] attempted to design a control device by a voluntary human motion. First, lifting up and putting down motions have been analyzed using a human model. Results show that torques in a hip joint and a knee joint are characteristic for control of the device. It means that EMG signals in front and back thigh muscles can become feature values because the muscles located there connect the hip joint and the knee joint. After that, a controller of the device using the EMG signals has been developed. Finally, artificial neural networks (ANN) have been introduced as a solution of the problem of individual differences.

Xiaopeng Liu et al in [20] developed a lower extremity exoskeleton for human performance enhancement at the Nanydng Technological University (NTU). Together with the exoskeleton linkages, an Exoskeleton foot has been designed to measure the human and the exoskeleton’s Zero Moment Point (ZMP). By using the measured human ZMP and the human leg position signals, the exoskeleton’s ZMP can be modified by trunk compensation.

D. S. Andreasen et al in [21] developed a prototype robotic system to facilitate upper extremity (UE) rehabilitation in individuals who sustain neuro-logical impairments such as cervical level spinal cord injuries (SCI), acquired brain injuries (ABIs) or stroke. A control system based on Electromyography (EMG) signals has been implemented to provide the appropriate amount of assistance or resistance necessary to progress a patient’s movement recovery.

Samuel K. Au et al in [22] proposed two control schemes to predict the amputee’s intended ankle position: a neural-network approach and a muscle model approach and tested these approaches using EMG data measured from an amputee for several target ankle movement patterns. The authors found that both controllers demonstrate the ability to predict desired ankle movement patterns qualitatively.

R. A. Bogey et al in [23] developed an electromyography (EMG) to force processing technique. Ankle joint moments and, by extension, ankle muscle forces were calculated. The ankle moment obtained by inverse dynamics was calculated for ten normal adults during free speed gait. It was found that there was a close correlation between inverse dynamics ankle moments and moments determined by the EMG to force processing approach.

Christian Fleischer et al in [24] presented a method to calculate the intended motion of joints in the human body by analysing EMG signals. Those signals are emitted out of the muscles attached to the adjoining bones during their activation. To allow a variety of different motions, a human body model with physical properties has been developed and synchronized with the data recorded from the pose sensors. Computation of the intended motion has been performed by converting calibrated EMG signals into muscle forces which animate the model. The algorithm has been evaluated with the help of experiments showing the calculated intended motion while climbing one step of a stair.

Christian Fleischer and Günter Hommel in [25] presented a body model of intermediate level of detail to allow prediction of the knee torque produced by thigh muscles based on EMG signals. The torque predicted was used as input for a torque controller that adapts the level of support offered to an operator by a powered leg orthosis.

Kazuo Kiguchi in [26] presented an effective human motion prediction method based on the EMG signals using a neuro-fuzzy technique for the control of power-assist exoskeleton robots.

Jan F. Veneman in [27] introduced a newly developed gait rehabilitation device. The device, called LOPES, combines a freely translatable and 2-D-actuated pelvis segment with a leg exoskeleton containing three actuated rotational joints: two at the hip and one at the knee.

Kazuo Kiguchi et al in [28] proposed a controller adaptation method to user’s EMG signals. A motion indicator has been introduced to indicate the motion intention of the user for the controller adaptation. The experimental results are encouraging and indicate the effectiveness of the proposed method.
H. Hel and K.Kiguchil in [29] proposed an electromyogram (EMG) based control (i.e., control based on the skin surface EMG signals of the user) for the exoskeleton robot to assist physically weak person's lower-limb motions. The skin surface EMG signals have mainly been used as the input information for the controller. In order to generate flexible and smooth motions and take into account the varying EMG signal levels according to the physical and psychological conditions of the user, fuzzy-neuro control method has been applied for the controller.

Sai K. Banala et al in [30] described the design and human machine interface of an Active Leg EXoskeleton (ALEX) for gait rehabilitation of patients with walking disabilities. The article proposed a force-field controller which can apply suitable forces on the leg to help it move on a desired trajectory.

Changmok Choi and Jung Kim in [31] presented the design of an assistive real-time system for the upper limb disabled to access a computer via residual muscle activities without standard computer interfaces (e.g. a mouse and a keyboard). For this purpose, electromyogram (EMG) signals from muscles in the lower arm were extracted and filtered using signal statistics (mean and variance). six patterns were classified, applying a supervised multi-layer neural-network trained by back propagation algorithm, In order to control movement and clicking of a cursor from the obtained signals, In addition, an on-screen keyboard was developed, making it possible to enter Roman and Korean letters on the computer. Using this computer interface, the user can browse the Internet and read/send e-mails.

Kazuo Kiguchi and Qilong Quan in [32] presented a muscle-model, which has been adjusted by a neuro-fuzzy modifier according to the user’s upper-limb posture. This model was introduced to realize an effective EMG-based controller of the power-assist exoskeleton. Force/torque generated between the user’s wrist part and the tip of the exoskeleton has been used to train the neuro-fuzzy modifier.

Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos in [33] presented a methodology for estimating the human arm motion and force exerted, using electromyographic (EMG) signals from the muscles of the upper limb. The proposed method is found to be capable of estimating motion of the human arm as well as force exerted from the upper limb to the environment, when the motion is constrained. Moreover, it was found that the method can distinguish the cases in which the motion is constrained or not (i.e. exertion of force versus free motion) which is of great importance for the control of exoskeletons.

R. A. R. C. Gopura and Kazuo Kiguchi in [34] proposed an EMG-based fuzzy-neuro control method for a three degree of freedom (3 DOF) human forearm and wrist motion assist exoskeleton robot (W-EXOS). The W-EXOS assists human forearm pronation/ supination motion, wrist flexion/extension motion and ulnar/ radial deviation. The paper presented the EMG-based fuzzy-neuro control method with multiple fuzzy-neuro controllers and the adaptation method of controllers.

Khalil Ullah and Jung-Hoon Kim in [35] proposed a new mathematical model for mapping the EMG to joint torque. This model has some unknown adjustable parameters, and the values of these parameters are obtained using non-linear regression.

Y. Y. Huang et al in [36] studied the EMG signals based on hand motions for specified tasks, and different gripping conditions so as to identify patterns of EMG signals. This will allow therapists to identify weak muscles of patients with motor weakness, such as spinal cord injury (SCI) and post-stroke and concentrate on rehabilitation activities which can strengthen these specific muscles. At the same time, it is envisaged that the analysis will yield useful data for objective and quantitative assessment towards control applications on the hand rehabilitation device, which is being developed.

Takeshi Ando et al in [37] developed the exoskeleton robot for tremor patients. In this paper, authors focused on the development of a signal processing method to extract the voluntary movement from the electromyogram (EMG) signal in which the voluntary movement and tremor were mixed. Authors have researched about following two methods to recognize the voluntary movement: one is the Low pass filter and neural-network (NN), and the other is the Short Time Fourier Transform and NN. The first method was found to be effective for recognition of healthy subject's movement.

Massimo Sartori et al in [38] presented a bio-mechanical model, a possible solution capable of predicting joint torque from the surface electromyography signals emitted out of muscles during their activation. The main objective of the research is to investigate the benefits and efficacy of this model and to lay down the basis of the current research, whose goal is to make possible a rehabilitation process either with active orthoses or virtual reality.

Daniel P. Ferris and Cara L. Lewis in [39] developed a pneumatically-powered lower limb exoskeletons for human physiology, and re-training motor deficiencies. One way to control the exoskeletons is with proportional myo-electric control, effectively increasing the strength of the wearer with a physiological mode of control. Healthy human subjects quickly adapt to walking with the robotic ankle exoskeletons, reducing their overall energy expenditure. Individuals with incomplete spinal cord injury have demonstrated rapid modification of muscle recruitment patterns with practice, walking with the ankle exoskeletons.

Mitsuhiro Hayashibe in [40] discussed about EMG-to-force estimation based on the physiological based muscle model in voluntary contraction. In addition to Hill macroscopic structure, a microscopic physiology originally designed by Huxley has been integrated. Authors have already developed the physiological based muscle model for the use of functional electrical stimulation (FES) which can render the myo-electrical property also in microscopic scale.

Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos in [41] developed the control interface between the user and a robot arm making use of electromyographic (EMG) signals from muscles of the human upper limb. A mathematical model has been trained to decode upper limb motion from EMG recordings, using a dimensionality-reduction technique that represents muscle synergies and motion primitives. It has been shown that a 2-D embedding of muscle activations can be decoded to a continuous profile of arm motion representation in the 3-D Cartesian space, embedded in a 2-D space. The system is used for the continuous control of a robot arm, using only EMG signals from the upper limb.

Jun Ueda et al in [42] proposed a novel method, named "individual muscle-force control" using a wearable robot (an exoskeleton robot, or a power-assisting device) to obtain a wider variety of muscle activity data as compared to standard motor tasks, e.g., pushing a handle by hand. A computational algorithm systematically computes the control commands to a wearable robot so that a desired muscle activation pattern for target muscle forces is induced. It also computes an adequate amount of a force in a proper direction that a person needs to exert against a handle by his/her hand. This individual muscle control method enables the users (e.g., therapists) to efficiently conduct neuromuscular function tests on target muscles by arbitrarily inducing muscle activation patterns.

S. Parasuraman and Arif Wicaksono Oyong in [43] built a stroke rehabilitation system using socially inspired robot technique. The system monitors patient's muscle activity and uses this information to drive an exoskeleton robot that will assist the patient to his/her arm. Movement is generated based on voluntary muscle activity by the patient and therefore will improve the patient's learning curve. Another main advantage is that the system minimizes the patient's inconveniences due to movement by robot. The system is based on torque feedback control. A sliding mode control was implemented in place of conventional control. The main advantage of sliding mode control over conventional control is its robustness. Sliding mode control does not require precise mathematical model of the system and it is insensitive to parametric changes and uncertainties within the system.

Sha Ma et al in [44] presents a study on developing EMG as an important interactive tool in a Virtual reality (VR) based system for hand rotation and grasping motion rehabilitation. The input interface includes an EMG system and a real-time magnetic motion tracking system, and the output interface is a PC monitor. The developed EMG bio-feedback based VR system enables the user to interact with virtual objects in real-time with multiform feedback.

E. Ceseracciu et al in [45] investigated the suitability of Support Vector Machine (SVM) classifiers for identification of locomotion intentions from surface electromyography (SEMG) data. A phase dependent approach, based on foot contact and foot push off events, was employed in order to contextualize muscle activation signals.

Renaud Ronsse et al in [46] proposed a novel method for movement assistance that is based on adaptive oscillators, i.e., mathematical tools that are capable of extracting the high-level features (amplitude, frequency, and offset) of a periodic signal. Such an oscillator acts like a filter on these features, but keeps its output in phase with respect to the input signal. Using a simple inverse model, the authors predicted the torque produced by human participants during rhythmic flexion– extension of the elbow. Feeding back a fraction of this estimated torque to the participant through an elbow exoskeleton, the authors were able to prove the assistance efficiency through a marked decrease of the biceps and triceps electromyography. Importantly, since the oscillator adapted to the movement imposed by the user, the method flexibly allowed the authors to change the movement pattern and was found to be still efficient during the non stationary epochs.

M. Yochum et al in [47] presented a functional electrical stimulator allowing the extraction in real time of M-wave characteristics from resulting EMG recordings in order to quantify muscle fatigue. This system is composed of three parts. A Labview software managing the stimulation output and electromyogram (EMG) input signal, a hardware part amplifying the output and input signal and a link between the two previous parts which is made up from input/output module (NIdaq USB 6251). In order to characterize the fatigue level, the Continuous Wavelet Transform is applied yielding local maxima detection. The fatigue is represented on a scale from 0 for a fine shaped muscle to 100 for a very tired muscle.

K.Y. Tong et al in [48] developed a novel design of a hand functions task training robotic system for the stroke rehabilitation. It detects the intention of hand opening or hand closing from the stroke person using the electromyography (EMG) signals measured from the hemiplegic side. This training system consists of an embedded controller and a robotic hand module.

Milica M. Jankovi et al in [49] presented a system for polymyographic analysis which addresses detection of muscle fatigue and strategies assumed by the central nervous system to deal with it. The system consists of EMG amplifiers, force transducers, A/D converter, portable computer and software used in the LabView environment that allows real-time and detailed offline processing of EMG signals in time and frequency domains.

Qichuan Ding et al in [50] developed an EMG-driven state-space model to estimate joint angular velocities and angles throughout elbow flexion/extension. The state equation of the model combines the Hill-based muscle model with the forward dynamics of joint movement, and expresses the kinematic variables as a function of neural activation levels. EMG features including integral of absolute value and waveform length have been extracted, and two quadratic equations which associate the kinematic variables with EMG features have been fitted to represent the measurement equation. Based on the proposed model, the joint angular velocities and joint angles were estimated using the EMG signals with the Extended Kalman Filter (EKF), and the estimated results have been used to control a manipulator.

Changmok Choi et al in [51] developed an alternative computer interface using surface electromyography (SEMG) for individuals with spinal cord injuries (SCI) to access a computer. Authors designed the interface to make a cursor move on a two-dimensional screen and to click using only three muscles: the extensor carpi radialis (RECR) and extensor carpi ulnaris (R-ECU) of the right forearm and the extensor carpi radialis (L-ECR) of the left forearm. In addition, a user can voluntarily control the cursor movement speed by modulating muscle contraction levels.

Yoshiaki Hayashi and Kazuo Kiguchi in [52] proposed the perception-assist for a lower-limb power-assist exoskeleton robot. In the daily life routine, it is obvious that walking is very important for persons to complete desired tasks. Basically, the robot assists the user’s muscle force according to the user’s motion intention which is estimated with the help of EMG signals. If the robot has found problems which might lead the user to dangerous situations such as the falling down, the robot tries to modify the user's motion in addition to the ordinal power-assists to make the user walk properly. Since, the user might fall down by the effect of the additional modification force of the perception-assist, and the robot automatically prevents the user from falling down by considering Zero Moment Point (ZMP).

Wietse van Dijk et al in [53] developed a passive exoskeleton that was designed to minimize joint work during walking. The exoskeleton makes use of passive structures, called artificial tendons, acting in parallel with the leg. Artificial tendons are elastic elements that are able to store and redistribute energy over the human leg joints.

Panagiotis K. Artemiadis et al in [54] analyzed the human arm manipulability and in doing so, its effect on the recruitment of the musculo-skeletal system has been explored. It was found that the recruitment and activation of muscles are strongly affected by arm manipulability. Based on this finding, a decoding method has been built, in order to estimate the force exerted in the three-dimensional (3D) task space from surface ElectroMyoGraphic (EMG) signals, recorded from muscles of the arm. The proposed method makes use of the manipulability information for the given force task.

Hardeep S. Ryait et al in [55] reviewed the historical developments in three main sections. First part describes the EMG signal properties. Second part deals with the mathematical models developed till now for EMG signal analysis. In the third part different design approaches have been reviewed for artificial hand.

III. CHALLENGES AND FUTURE SCOPE

The main challenges for the design of exoskeleton robots are good mechanical strength, less weight, sufficient grip force, low power consumption, computational capability compatible to control scheme and high speed of operation [55].

The design of structure is one area where an imaginative design may reduce lot of stress from weight constraint. The grip force and power consumption can be taken care by the proper choice of the actuators [55].

The ideal requirements are material for mechanical structure having mechanical strength, flexibility and weight like bone, the controller having computational capability, speed and adaptability like brain, actuator having high torque and flexibility like muscles, and the feedback elements having sensing capability like skin [55].

EMG is a relatively new technology. It has a definite potential to be used as control signal for multifunction prosthesis. There is need to draw correlation between the physiological, physical factors and the EMG signal [55].

Coming area of human machine interface is believed to be based on EMG technologies. A vast contribution is need, which this paper is an attempt as motivation to new researchers [1] [55].

Advanced algorithms need to be developed to extract useful neural information [1].

One of the innovative aspects is the combined use of electroencephalogram (EEG) and electromyography (EMG) to relay information for controlling the lower-limb exoskeleton [1].

IV. CONCLUSION

Although the research on exoskeleton robots started since 1960s, the research on sEMG (Surface ElectroMyographic) signal based exoskeleton robots started a decade ago only. After reviewing the literature we concluded that

- The biomimetic EMG-controller demonstrated a smoother and more natural movement pattern.
- EMG-to-force processing could be used to estimate muscle moments or forces during walking with a reasonable degree of accuracy.
- Electromyogram (EMG) signal (0.01-10mV, 10-2,000Hz) is one of the most important biological signals which directly reflect human muscle activities since it is generated when the muscles contract. The EMG-based control (i.e., control based on the skin surface EMG signals of the user) is one of the most effective control methods for many kinds of assist robotic systems especially for the power-assist exoskeleton robots, since EMG signals of user's muscles directly reflect the user's motion intension.
- Two kinds of EMG-based control method can be considered to control the exoskeleton robot in order to assist the user's motion. One is the EMG-based neuro-fuzzy control method (i.e., a combination of fuzzy control method and neural network control method). Although this control method is effective, the control rules become complicated if the degree of freedom of the power-assist is increased. The other is the muscle-model-oriented EMG-based control method in which torque for power-assist is obtained using a matrix that relates the user's joint toque with certain muscle activities.
- EMG-based control (i.e., control for power-assist based on user's EMG signals) is not very easy to be realized for multi-DOF power-assist exoskeletons because
  (a) obtaining the same EMG signals for the same motion is difficult even with the same person,
  (b) activity level of each muscle and the way of using each muscle for a certain motion is different between persons,
  (c) real time motion prediction is not very easy since many muscles are involved in a joint motion such as a shoulder joint motion,
  (d) one muscle is not only concerned with one motion but also another kinds of motion,
  (e) activity of antagonist muscles affects the generated joint torque,
  (f) the role of each muscle for a certain motion varies in accordance with joint angles (i.e., the posture change affects the role of each muscle for a certain motion), and
  (g) The activity levels of some muscles such as bi-articular muscles are affected by the motion of the other joint.

There is a great need of a reliable, robust and precise control scheme for the Myoelectric control of an Exoskeleton robots, so that it can be implemented in real-time.

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