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A review on EMG-based motor intention prediction of continuous human upper limb motion for human-robot collaboration

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ABSTRACT

Electromyography (EMG) signal is one of the widely used biological signals for human motor intention prediction, which is an essential element in human-robot collaboration systems. Studies on motor intention prediction from EMG signal have been concentrated on classification and regression models, and there are numerous review and survey papers on classification models. However, to the best of our knowledge, there is no review paper on regression models or continuous motion prediction from EMG signal. Therefore, in this paper, we provide a comprehensive review of EMG-based motor intention prediction of continuous human upper limb motion. This review will cover the models and approaches used in continuous motion estimation, the kinematic motion parameters estimated from EMG signal, and the performance metrics utilized for system validation. From the review, we will provide some insights into future research directions on these subjects. We first review the overall structure and components of EMG-based human-robot collaboration systems. We then discuss the state of arts in continuous motion prediction of the human upper limb. Finally, we conclude the paper with a discussion of the current challenges and future research directions.

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1. Introduction

Robots have a wide range of applications and, currently, they are entering into the daily life of humans [1]. The advancement of robotic research and technology has brought them from a confined to shared environment. As a result, a close interaction of a human and robot has been considered as a practicable issue. Humans and robots can interact through various methods that are varied in the level of interaction and in the degree of sophistication [2,3]. The different modes of interaction can be defined as manual, shared or co-activity, and autonomous modes [4,5]. In manual or autonomous interaction modes, a robot or human complete a given task independently. In other words, the robot provides no assistance to the human during the manual mode and the human provides no assistance to the robot during the autonomous mode.

An automated system could be appropriate for precision and repetitive tasks in structured environments but may not be suitable for some tasks in unstructured environments that require abilities of fast judgment, flexibility, and adaptation. Although humans can provide such abilities, their limited load capacities can make manual operations difficult. As a result, there are some cases of tasks, where both manual and autonomous systems could be inappropriate. Instead, such tasks require cooperation or collaboration between the human and robot within the shared mode of interaction.

The current development in sensor technology has made the interaction of robots and humans more effective. As a result, a human and robot can perform a given task in cooperation or collaboration through various modes of communication. Although the terms of collaboration and cooperation are mostly used interchangeably in human-robot interaction studies, conceptually, they are different. During cooperation tasks, robot and human partners interact without the need to know what the other is doing in a shared task. However, during collaboration tasks, both partners should communicate with and understand each other and it requires a high level of interaction [5–7].

Human-robot collaboration is a broad research field that can be applied in diverse areas, such as manufacturing operation [8], teleportation application [9], intelligent vehicles and aircrafts [10], entertainment and education [11], assistive and rehabilitation techno- logy [12] and robot-assisted surgery [13]. Human-robot collaboration systems can improve productivity, enhance the quality of tasks, and reduce the workload of humans [14,15]. Close interaction and best performance can be achieved when the partners can efficiently communicate with and understand each other [16]. One of the challenges in collaboration systems is the ability to estimate human intentions so that the robot reacts to his/her intentions naturally while preserving the safety of its human partner. Both a human and robot need to understand the current state of their partner and be able to predict what they will do next in shared tasks [17].

An intention, which is a desire of subjects to accomplish something, could be either explicit or implicit. The former involves the purposeful conveyance of information, while the latter involves the involuntary conveyance of information about emotional and contextual states, such as facial expression [18]. In implicit intentions, the cue generated by the human is not primarily aimed to interact with the robot, but the robot can use the cue to infer the intention of the human. The core goal of intention prediction in collaboration systems is to give robots some intelligence so that they are capable to read human emotion or action. Consequently, they can communicate implicitly with their human partner to modify their action and adapt to human action [19–22].

There are various signals to facilitate the communication between a human and robot. Researchers have used different modes of intention inference, such as head pose, eye gaze, hand position and orientation, speech, kinematic parameters (such as velocity and force), and biological signals. In general, the signals that are utilized for intention prediction could be categorized as biological and non-biological signals [23–27]. Human body generates various biological signals, such as Electrooculogram (EOG) [28], Electrocorticogram (ECoG) [29], Electroencephalogram (EEG) [30], Magnetoencephalography (MEG) [31], and Electromyogram (EMG) [32]. Recently, these signals have been widely used in human-robot collaboration systems to predict the intention of the users [33,34]. To make this paper manageable, we focus here on EMG-based motor intention prediction for human-robot collaboration systems.

EMG signals are acquired as bio-electric signals generated from muscle cells and have a wide range of applications, such as in rehabilitation and assistive technologies, ergonomics, clinical diagnosis, and sport science [32]. In several robotic applications, especially in human-robot collaboration systems, EMG signal is used as a signal for intention prediction of human motion. Most importantly, it is used to estimate the kinematics of upper limb movements, which are the most active parts of human body and vital for daily activities [35–38].

The EMG-based intention prediction of human motion can be broadly categorized as classification and regression models. Many researchers have been focused on discrete motion control from the signals, and there are numerous survey papers on classification models, including the work by Ahsan et al. [39], Chowdhury et al. [40], and Oskoei et al. [41]. Although the estimation of continuous human motor intention from EMG signal and its application are currently the hot issue in EMG-related research activities [42], to the best of our knowledge, there is no review paper on continuous human motion estimation from the EMG signal. Hence, for the remainder of this paper, we will focus on the EMG-based motor intention estimation of continuous human upper limb motion. Though the term EMG-based continuous motion estimation is referred as *proportional myoelectric control* [43] in prosthetic control systems and related studies, we prefer the former term to address the wider application of EMG-based control systems.

In this paper, based on a survey of over 100 related papers, we present a comprehensive review of EMG-based motor intention prediction of continuous human upper limb motion, including the models and approaches used in continuous motion estimation, the motion kinematics estimated from EMG signal, and the performance metrics utilized for system validation, and provide some insights into future research directions on these subjects.

The contribution of this review is threefold: 1) we present a comprehensive review on the overall structure and components of EMG-based collaboration systems with focus on the continuous motion of human upper limb; 2) we provide a comprehensive review on the state-of-the-art methods and techniques in continuous motion prediction of human upper limb, and its application in human-robot collaboration systems; 3) we discuss current challenges and future research directions of EMG-based continuous motor intention prediction of human upper limb.

The remainder of the paper is organized as follows: Section 2 discusses the complete system of EMG-based human-robot collaboration systems; Section 3 presents continuous upper limb motion prediction from EMG signal; Section 4 presents discussion and conclusion of the paper.

2. EMG-based human-robot collaboration system

A human-robot collaboration system allows a human and robot to complete a shared task in a way that the robot responds to the intentions of the human, and at the same time, preserves the safety of its partner. Hence, communication and understanding of the partner, keeping the safety of the partner, mutual trust and, adaptation, are the defining features of such systems. Above all, communication among the partners is an indispensable element of a human-robot collaboration system.

As shown in Fig. 1, a human-robot collaboration system, which is focused on the EMG-based continuous human motion prediction, consists of human, EMG signal processing technique, intention prediction model/algorithm, robot and its control mechanism, and tasks to be executed (application). In this system, the EMG signal serves as a communica-tion mode between the human and robot.

The EMG signal is acquired from a human upper limb and it is utilized to convey his/her intention to a robot so that both partners collaboratively perform a given shared task. During the execution of the task, the robot is communicated with the human through various feedback mechanisms. Hence, a reliable and robust control strategy ensures a smooth communication between the human and robot partners.

2.1. Upper limb motion

The motion of the human upper limb is complex and involves the interaction of the nervous systems, musculoskeletal systems, and its surroundings. Human upper limb offers several degrees of freedom (DOF), and its movement requires the coordination of different joints that consist of a wide range of motion. It involves shoulder, elbow, wrist, and finger joints to perform a set of activities of daily life. To make the scope of this paper more specific, we excluded the review on finger motion.

Shoulder motion has three DOFs (i.e., abduction/adduction, flexion/ extension, and internal/ external rotation). Elbow joint allows two DOFs (i.e., flexion/ extension and supination/ pronation). The wrist joint has two DOFs (i.e., flexion/extension and radial/ulnar deviation) [44]. Each muscle in the upper limb includes many motor units. The motor unit consists of a motor neuron and numerous muscle fibers, which are varied by numbers across human muscles. The muscle fibers of each motor unit are interconnected with fibers of other motor units so that fibers belonging to several motor units are close to each other. Neural and muscle cells are excitable cells that can produce a change in the potential across the membrane, which separates the cell from the environment. If the application of an external stimulation to their membrane leads to depolarization and the depolarization reaches a certain threshold value, then an action potential is produced.

Human upper limb motion is so redundant that there are infinite numbers of possible paths even for a simple task, such as reaching a target in unconstrained environments. However, the redundancy can be taken as a beneficial feature because it provides more flexibility to carry out complex tasks [45]. There are various studies on minimizing the range of actual trajectories based on the optimal rules, such as minimum-jerk model and inverse optimal control [46]. Most of these optimization rules are focused on at optimizing one or more specific features of the movement. However, human motor control may care about overall task characteristics instead of optimizing one or more of the features.

During upper limb motion, a range of different limb trajectories and associated movement patterns are involved. Hence, parameters (such as kinematics and models of joints or segments, the range of motion, activities, and assumptions and algorithms involved) are needed to be defined [47]. Some factors, which affect the movement tasks (such as width and height of the reaching motion and loading condition) should also be considered [48].

2.2. EMG signal processing

EMG signal can be used for numerous applications, including assistive and rehabilitation robotics [49,50], ergonomics [51], diagnosis and clinical application [52], sport science and motion analysis [53,54], telerobots [55], military task [56], and etc. Some of these applications (such as assistive and rehabilitation robots, and telerobots) may involve the shared mode of interaction of human and robot partners; hence, they can be categorized as a human-robot collaboration system.

The advantageous features of EMG signal that make it valuable for motion study include its simplicity in acquisition as well as processing, the development of wireless and wearable electrodes, the provision of fast and practical communicating control commands to artificial systems. It can give information about the intention of motion about 50–100 ms before the motion actually happens and is used in interfaces, where intention prediction is required within this prediction horizon [42]. Moreover, it is useful for making user upper limb free of bulky interface sensors.

However, its dependency on the anatomy, instrument, methods, and procedures used in the system, is the main limitation of the signal. Besides, different artifacts and crosstalk affect the quality of signal and thereby affect the interpretation of intention from the signal [57–59]. However, in an effort to overcome some of the mentioned limitations, various signal processing techniques and tools have been developed. Since EMG signal is generated as a result of human muscle activity, it is a reliable source of signal for muscle-related studies and for the development of human-robot collaboration systems on the basis of human upper limb motions [60]. In this system, it can provide information on arm and hand motion to predict the intention of the human, which can be modeled as a classification or continuous motion.

As shown in Fig. 1, the stages to use EMG signal for human motion intention prediction thereby controlling a robotic device can be identified as 1) signal acquisition, 2) signal preprocessing, and 3) feature extraction. Although some of the techniques used in each stage might be slightly different between classification and continuous motion estimation models, the basic principles are common for both models [61,62].

2.2.1. EMG signal acquisition

Signal acquisition stage requires a critical attention as the subsequent processes and the accuracy of continuous motion parameter estimation primarily depends on the quality of the signal. This stage mainly involves considering the method used to record the signal, acquisition device, number of channels and position of muscles, amplifier and filter design, sampling rate, and data transmission approaches [32].

The electric potential generated by muscle cells are recorded either as intramuscular electromyography of surface electromyography [63,64]. On one hand, intramuscular EMG records the electrical activity of a muscle by inserting a needle or wire elec-

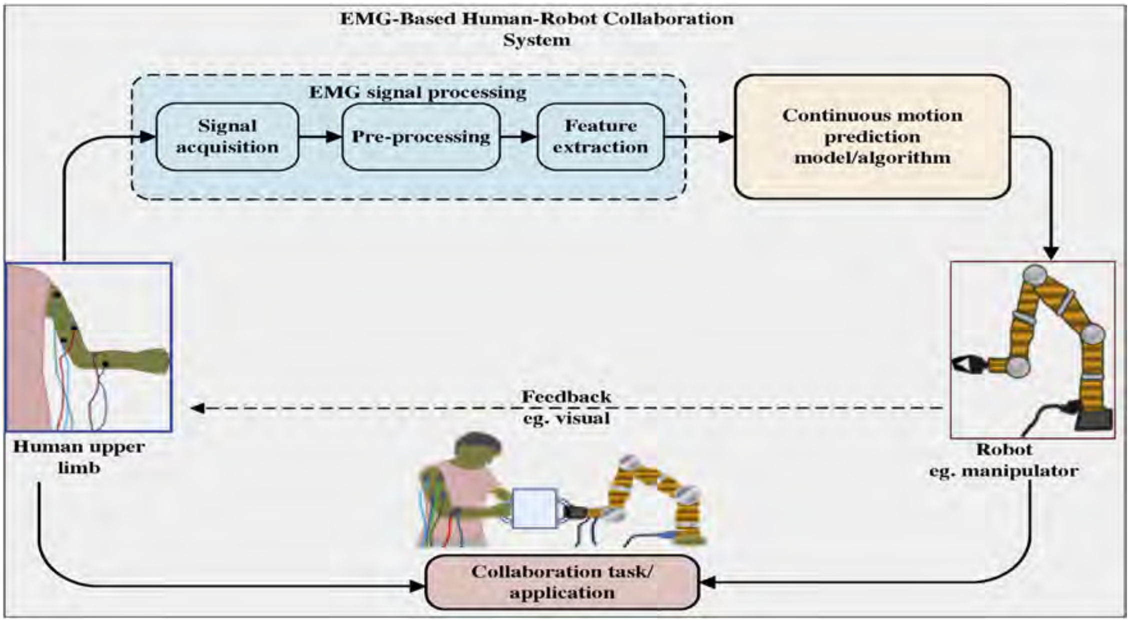

Fig. 1. EMG-based intention prediction of continuous human upper limb motion for human-robot collaboration systems.

trode through the skin into the muscle, while surface EMG records muscle activity from the surface of the skin above the muscle. Although intramuscular electromyography is an invasive method and usually used in a clinical application, it can be a potential to be used as an intention prediction signal to control intelligent robotic devices, especially for assistive technologies [65,66]. On the other hand, surface electromyography is a non-invasive method and widely utilized for application of human-robot collaboration systems [57]. The combination of the two acquisition modalities can also be used in intention prediction. For instance, Kamavuako et al. [67] reported that their combination improved the accuracy of prediction of upper limb motion. Throughout this paper, the term EMG is used to express the surface EMG, unless otherwise explicitly expressed as intramuscular EMG.

On the bases of electro-chemical behavior, EMG electrodes can be polarizable or non-polarizable. Non-polarizable silver–silverchloride (Ag/AgCl) electrodes are highly stable and preferred for EMG measurements [68]. Monopolar, bipolar, and array electrodes are the most common electrode configurations used in sEMG interfaces [69]. Compared to bipolar electrodes, the monopolar configuration is more sensitive to changes in muscle activity with increases in force [70]. Staudenmann et al. [71] reported that the use of full high-density EMG grid in a bipolar way, compared to conventional bipolar electrodes, significantly improves force estimation. Electrodes vary in shapes, such as circular, rectangular, and square electrodes. Circular electrodes that can vary from 1 mm^2 to a few cm^2 in sizes, are widely used [69,72]. The benefit of large electrodes is that it is less sensitive to electrode shift [73]. However, the influence of the electrode size and shape on the EMG signal is insignificant.

EMG signals can be recorded both with wet and dry electrodes. The wet electrodes use conductive electrolyte gel between the electrode and skin, whereas the dry electrodes do not need any gel. In the wet electrode, before applying the gel, it is required to prepare the surface of the skin, such as clean and shave any excessive hairs. Currently, wearable acquisition devices are developed and many of them are based on dry electrodes. Increased user comfort, minimized preparation time, and portability are the advantages of this devices, although their signal to noise ratio is lower compared to the wet electrode technique [32].

Selecting an appropriate number of EMG channels and electrode positions are another important issues to be considered in signal acquisition [74–77]. The number of channels and electrode positions can be selected either on the basis of physiological and anatomical knowledge of skeletal muscles or some statistical optimization techniques. Since the DOFs to be studied can require the coordination of two or more muscles, understanding the nature of the motion for the determination of muscle positions is critical.

During real-time applications, electrodes may shift from the designated part of the muscle (i.e, because of dynamic changes in the human body) or may lose contact with the surface of the skin. This encounter reduces the amplitude of the measured signal and thereby affects the accuracy of prediction. Detection of signal failure, which is caused by electrode shift or lose, is a challenging task, and various methods have been proposed to address this challenge, such as human movement modeling [78]. The use of high-density EMG, which is insensitive to electrode shift, can reduce the effects of electrodes shift and maintain a high performance even when some electrodes are omitted [79,80].

The quality of the measured EMG signal can be described by the ratio of the measured EMG signal to unwanted noise contributions from the environment. High-quality signal provides more of the required information for intention prediction so that it increases the accuracy of prediction. However, noises from various sources are inevitable and can contaminate the recording of EMG signals [57,81–83]. In this regard, amplifiers are designed and applied to reject or eliminate the noises in order to maximize the signal to noise ratio [84–86].

The other procedure in the signal acquisition is the conversion of the signal from the analog to digital form by analog to digital converters. The choice of an optimal sampling rate is an important issue to avoid both under-sampling and oversampling [86–88]. The sampling rate of 1000 Hz with a low-pass filter at 400–450 Hz is commonly used in EMG recordings. Li et al. [89] investigated the effects of sampling rate on the accuracy of classification model on arm and hand movements. Only a slight decrease in accuracy was found when the sampling rate was decreased from the commonly used values. A similar result was also reported in [88]. However, we could not find any research paper that investigates its effect on continuous motion prediction as it might not be explored. The signal that is acquired through the above processes and methods is the unprocessed or raw signal, and several processing techniques can be applied on the signal to utilize it for the intended purposes.

2.2.2. Preprocessing

At the very beginning of the preprocessing stage, it can be required to check the raw EMG signal for baseline offset. Baseline offset can be adjusted during the signal acquisition process, like the work by Tomasini et al. [90], who proposed a digitally controlled system for EMG signal acquisition with zero-offset. However, the raw EMG signal may have a baseline offset from zero, and usually, the raw signal is corrected for baseline offset by subtracting the mean EMG amplitude from every data value. Frey et al. [91] proposed another approach, which is a nonlinear error modeling that corrects EMG signal as a nonlinear function of both baseline and measured signal amplitude. Rectification is another important preprocessing procedure to extract EMG envelope modulation [92]. Though the full-wave or half-wave rectification of EMG signal could be obtained, full-wave rectification is widely used and preferable (because it retains all of the signal energy) to estimate upper limb motion from EMG signal.

Despite the necessary caution in the acquisition process, some noises and artifacts could be super-imposed on the raw EMG signal. Thus, there is a need to design a filter to smooth the signal or reduce the noises. The filter type, order, and cutoff frequency are among the important factors to be considered during the design of a filter. Several researchers have used a low-pass filter of Butterworth with a cut off frequency ranging from 2 Hz to 20 Hz, while predicting continuous upper limb motion parameters [93–97].

Other advanced EMG processing techniques for the removal of noises and artifacts include signal whitening [98], independent component analysis (ICA) [99–101], empirical mode decomposition (EMD) [102,103]. Although these techniques are capable of improving the accuracy of motion prediction, they are computationally expensive [104,105]. Currently, some processing tools with low computational load have been proposed, such as the work of Hayashi et al. [106] who proposed variance distribution estimation based on marginal likelihood maximization.

2.2.3. Feature extraction

To estimate continuous motion parameters for real-time applications, the analysis is performed on time segments or windows. Both adjacent windowing and overlapped windowing techniques can be used. However, the overlapped window approach is preferable as it can reduce controller delay. Usually, there are three types of features in EMG control systems: a) time domain, b) frequency domain, and c) time-frequency domain [107–109].

Time Domain Features: The time domain features are computed directly from raw EMG (i.e., without any transformation), and the resultant values are given as a function of time [109]. Compared to the other features of EMG, they involve a lower computational complexity and thus have been widely used in both classification and regression models. The commonly used time domain features include mean absolute value (MAV), integrated electromyogram (IEMG), root mean square (RMS), zero crossing (ZC), slope sign changes (SSC), waveform length (WL), and etc. Several combinations of these time domain features are usually used in continuous motion estimation. However, most of the features are redundant, and hence combining some of the features may not result in significant improvement in the accuracy of prediction than using either of them [109]. The question of which feature or combination of features can result in the best prediction accuracy for a model is usually a trial-and-error approach, which is required to compare the performance of several alternatives.

Frequency Domain Features: The frequency domain features are extracted by using estimated power spectrum density and are computed by parametric methods. However, these features in comparison with time domain features require more computational cost. The commonly used frequency domain features of EMG signal include auto-regressive coefficients (AR), power spectrum (PS), mean frequency (MNF), median frequency (MDF), frequency ratio (FR), and etc.

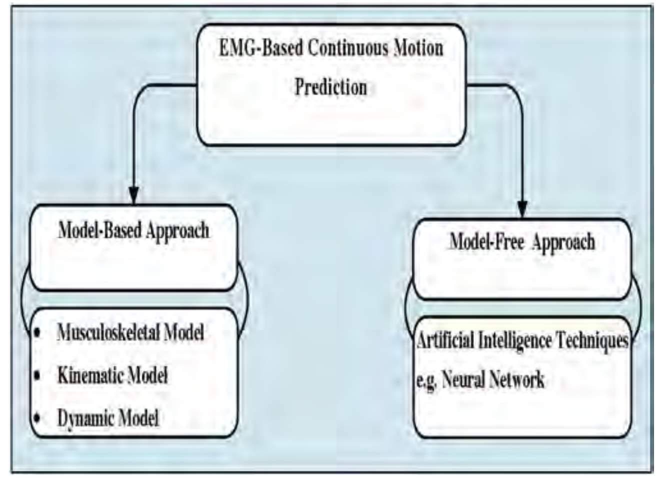

Fig. 2. EMG-based continuous motion prediction approaches.

Time-Frequency Domain Features: Time-frequency representation can localize the energy of the signal both in time and in frequency. However, these features generally require a transformation that could be computationally expensive. Some of these features include short time Fourier transform (STFT), wavelet transform (WT), and etc.

The combinations of time domain and frequency domain features can also be used. Yamanoi et al. [110] used the mean absolute value and power spectrum features to predict hand posture and grip force. Similarly, Artemiadis et al. [111] used the combination of time domain and frequency domain features for real-time arm motion estimation. Siddiqi et al. [112] reported that the frequency-domain features performed better than the time-domain features in the prediction of thumb angle and force during flexion motion. Nlandu et al. [113] compared the performance of different combinations of nine features extracted from intramuscular EMG recordings for the estimation of grasping force. Apart from this, to the best of our knowledge, there is no comprehensive research on the influence of different features or combination of features of EMG on the performance of continuous motion prediction.

2.3. Continuous motion prediction model/algorithm

We categorized the EMG-based continuous motion prediction approaches for human upper limb movements as model-based and model-free approaches, as shown in Fig. 2. The model-based approach comprises of kinematics models [114], musculoskeletal models [115] or dynamic models. The model-free based approach utilizes artificial intelligence method, such as neural network.

2.3.1. Model-based approach

In the model-based approach, a linear or nonlinear analytical relationship is established between inputs and outputs. The relationship may consider several unknown parameters of the inputs that contribute toward the prediction of the target output, e.g, wrist position. These parameters could be first identified either through experiments or some assumptions. Then the parameters are adjusted repeatedly until the desired performance of the model is achieved. In the model-based approach, the relationship between EMG signal (i.e. input) and desired motion parameters (e.g, force, acceleration, and position) can be expressed as a kinematic, dynamic or musculoskeletal model.

Kinematic model: In upper limb studies, a kinematic model represents human arm motions as kinematic chains of rigid body parts. It requires the anatomical and functional knowledge of the upper limb, and it is the bases to understand human upper limb motions. The segments are upper arms, forearms, and hands, while the joints are shoulder, elbow, and wrist. Markers can be used to define the position and orientation of the segments [114]. Usually, the kinematic chain is modeled as 7-DOF limb models, by excluding fingers motion. Three degrees of freedom at the shoulder are elevation plane, thoracohumeral angle (elevation angle), and shoulder rotation; the two degrees of freedom at the elbow are elbow flexion and forearm rotation; the two degrees of freedom at the wrist are flexion and deviation.

However, the main problem associated with this approach is that an accurate representation of human upper limb is challenging. Because human upper limb is irregular in shape and made of inhomogeneous and nonlinear materials, it is usually difficult to accurately represent the relationship between the input and targeted output. The kinematics model mainly aims to find parameters, such as positions, orientations, velocities, and accelerations. To obtain the positions of the joints, techniques (such as forward and inverse kinematics) have been employed [114].

Dynamic modeling: Dynamic modeling of upper limb involves the determination of torque or force by considering the weight and force of the limb as an input to a function of inertia, Coriolis, centrifugal, and gravity vectors. Each of this function takes a kinematics of human arm (orientation, position, velocity and acceleration vectors) obtained from the kinematic model. In EMG-based upper limb motion analysis, the dynamic model is used in the estimation of torque and force from EMG signal.

Koike et al. [116] used a forward dynamics model acquired by an artificial neural network to reconstruct human arm movement from EMG signal. Clancy et al. [117] used linear and nonlinear polynomial model structures to estimate elbow torque from EMG signal. In their model, extension and flexion of EMG signals were related to joint torque by using four parameter dynamic model structures (i.e, Linear, Polynomial nonlinear, Hammerstein, and Weiner models). The parameters of the model were estimated by using the pseudo-inverse technique to regularize a least square minimization. Similarly, Liu et al. [105], Koirala et al. [93], and Hashemi et al. [118] used different types of dynamic models to estimate either torque or force from EMG signal.

Musculoskeletal Model: Several researchers have proposed musculoskeletal models from simple to complicated modeling approaches that involve different assumptions and analysis for the desired application. Hill-based muscle model is widely used as a musculoskeletal model to predict continuous motion from EMG signal. It predicts the force developed by the physiological muscle as a function of the neural activity level and joint kinematics (i.e, muscle length and velocity).

The challenges with this model include the redundancy of human muscles around joints and the changes in parameters (velocity and arm length). Despite its challenges, it can be used to build a quantitative relation between EMG signals and musculotendon forces. Wang et al. [119], first utilized Hill-type models to estimate muscle force from the predicted muscle activations. Then, they predict muscle moment by incorporating muscle geometry model along with the muscle forces.

2.3.2. Model-free approach

In this model, a numerical function, which is usually approximated by machine learning, is mapped between the input and desired target. The main problem of this approach is that the relationship between the input and output is unknown or a black box. Several artificial intelligence algorithms have been utilized to map an input set to an output set without consideration for any formulation of muscle functionality. Basically, in this approach, a large array of inputs and related outputs of a system were presented to the system. After the training period, the system is expected to predict the continuous motion parameter given a random EMG signal as the input set.

This approach is widely used for EMG-based continuous motion prediction. The various artificial intelligence methods to predict continuous human upper limb motion include the neural network model, fuzzy approximation, Bayesian network, hidden Markov model, and Kalman filter. Loconsole et al. [120] used time-delayed neural networks to estimate the joint torque of an active exoskeleton robot from MAV features of EMG signals. They used two different neural networks, one for elbow and the other for the shoulder torque estimation. However, they considered four directions (upward, downward, forward, and backward) alone along the sagittal plane. Nielsen et al. [121] used a multilayer perceptron artificial neural network to estimate force from four feature sets of EMG signal.

2.4. Control system

In the design of control system, the kinematics parameters estimated from EMG signal is fed into a robot to produce output commands. Once a robot knows human intentions through a motion kinematics, it acts according to the intention to achieve a shared goal. Such human robot-collaboration system requires the design of an appropriate control strategy that should aim to achieve the best performance, stability, and safety. Several kinds of EMG-based control methods have been proposed to control robots according to human intention. The control system could be categorized on the bases of model (such as dynamic and kinematic control), or hierarchy of control system (such as proportional and impedance control).

In assistive or assist-as-needed controllers, the robots help users to move their disabled or weakened upper limbs in the desired trajectory to reach a target or accomplish tasks, such as grasping. Teramae et al. [122] developed an assist-as-needed controller based on a model predictive control (MPC) approach. In their system, the robot only assists the deficient torque to generate a target movement to enhance the recovery of motor functions of patients. In such case, the accuracy of prediction may not be strictly necessary, because the user could gradually adapt to the system. Kiguchi et al. [123] proposed an impedance control method for an upper-limb power-assist exoskeleton robot. Moreover, they applied a neurofuzzy matrix modifier to make the controller adaptable to any users. Peternel et al. [124] proposed an adaptive exoskeleton control system, which is primarily a feed-forward control scheme. It dynamically adapts the shape of the robot joint torque trajectories in accordance to the human intention. In their proposed system, EMG was used to estimate the direction of torque change to minimize human effort. Kim et *al.* [125] developed an EMG-based variable impedance control for elbow exercise. However, the control system could not control the fluctuation of EMG level. Rahman et al. [37] proposed a nonlinear sliding mode control for exoskeleton that provides active assistance in arm movements.

Artemiadis et al. [111] proposed an inverse dynamic controller for manipulating an anthropo-morphic robot arm by using EMG signals from the muscles of the upper limb. The uniqueness of the proposed method is that it is not affected by EMG changes with respect to time. Similarly, Kwon et al. [126] proposed a proportional-derivative (PD) controller that uses a motion estimated from upper limb for human–machine collaboration. Generally, to utilize the benefits of EMG signal in human intention prediction for human-robot collaboration, it is necessary to develop a robust and reliable control system. Particularly, the control system should aim to address the sensitivity of EMG signal to time and across persons.

2.5. Human-robot collaboration application

The capability of a robot to recognize and predict the intention of the human provides it with the information to take action to help the human partner perform the shared tasks. Meanwhile, the safety is guaranteed (by prohibiting robot movement from unsafe conditions) and interaction with the human partner is enhanced.

Intention prediction from upper limb motions has several applications. Among collaboration systems, continuous human motion prediction has been widely used in assistive and rehabilitation technology. In this technology, it can help weak elder, disabled, and injured individuals to perform daily upper limb activities [127]. However, most of the application is concentrated on the development of exoskeleton and prosthetic robots [128–133]. There are a few researchers, who used the signal in the application of robotic manipulation [60,111,126].

Most of the applications of advanced models and algorithms of EMG-based interfaces have been confined to academic environments, and they have been rarely implemented in commercial systems. Dario Farina et al. [134] suggested that for widespread acceptance, especially for ideal prosthesis control, EMG-based interfaces should fulfill the criteria of being intuitive, closed-loop, adaptive, and robust to real-time control. In addition, the requirements for the minimum number of recording electrodes, minimum training, limited complexity, low consumption, and low sensitivity to repositioning should be considered.

Even though the above criteria are set from the perspective of assistive devices, they are valid for other human-robot collaboration applications. EMG signal is noninvasive, simple and intuitive, rich of neural information, and has a direct relation with a motion. These characteristics of the signal are a great potential to develop an EMG-based human-robot collaboration system, other than rehabilitation and assistive technology. Hence, the signal can be utilized in wider applications and technology, which could practically address the societal problems and improve quality of human life.

3. EMG-based continuous motion parameter prediction

The EMG signal characteristics can be influenced by physiological and non-physiological factors that cause subject-specific and non-stationary problems during movements. As a result, prediction of motion parameters from EMG signal is a challenging task. EMG can be utilized to estimate continuous human intention of both upper and lower limb motions. Since upper limb movement is quite functional and important in human daily life, its motion parameter prediction can be used in several human-robot collaboration applications. We will present the motion parameter prediction of shoulder, elbow, and wrist from different muscles eliciting such motions and the performance metrics of the prediction models. Studies show that the relationship between EMG and force is more linear than those between EMG and any other motion parameters. As a result, the prediction of kinematic parameters is more challenging and complicated than that of kinetic parameters. In one or other ways, several articles have discussed the prediction of kinetic models. Hence, we limited the topic of our review to kinematics motion parameter estimation.

3.1. Kinematics motion parameter estimation

Several methodologies have been proposed for the utilization of EMG signals to infer human motion intention, and thereby to control a robot that collaborates with a human. On the bases of the kinematics motion parameters, we systematically categorize the continuous motion parameter prediction of the human upper limb into two groups; the first group consists of acceleration and velocity prediction, and the second category consists of joint angle and position/ trajectory prediction. The parameters can be either directly or indirectly predicted from EMG signals. When the direct estimation approach is used to estimate parameters, the EMG is directly mapped to the desired output target. However, in case of indirect approaches, the desired output (e.g, acceleration) is the output of some parameters (e.g, force), which is in turn obtained from the direct mapping of EMG signals.

3.1.1. Acceleration and velocity prediction

The prediction of acceleration and velocity from EMG signal is not as common as the other parameters prediction. Usually, these parameters are not directly predicted from EMG signal. Instead, first forces are estimated from EMG signal and then the estimated forces are used to predict acceleration and velocity. Koike et al. [116] first, they estimated joint torques at the elbow and shoulder in the horizontal plane from the surface EMG signals of 10 flexor and extensor muscles. By using the estimated torques and actual joint kinematics, joint angle acceleration was estimated. Artemiadis et al. [128] estimated the angular velocity of shoulder and elbow motion by using a decoding model based on the state-space model from seven muscles of EMG signals. Simultaneously, their proposed approach is able to predict the exerted force by using a switching model.

Han et al. [135] and Ding et al. [133] first developed a model that combines the Hill muscle model and joint forward dynamics. Then, they used a state-space model for estimation of angular velocity from EMG signal. Raj et al. [136] tried to estimate angular velocity for three different speeds and angles of the forearm from EMG signals by using multi-layered perceptron neural network and radial bases function neural network model. However, the accuracy of the predicted parameter is not satisfactory.

3.1.2. Joint angle and position prediction

Since EMG signal is directly related to muscle forces but not positions, its use to infer arm positions could be indirect. As a result, two approaches have been used. The first approach is that acceleration is predicted from force/torque, which is estimated from EMG signal, and this acceleration is used to predict joint angle/position [116]. The other approach is that EMG signal is directly mapped to joint angle/ position by using an artificial neural network model.

The prediction of single joint angle or position is easier than that of multiple joints, and better performance can be achieved. Yu et al. [96] assumed that EMG signal is quasi-stationary instead of a non-stationary signal to obtain pre-angle values from the raw synergistic EMG signal and to estimate the joint angle through normalization. They proposed a third-degree polynomial and optimization algorithm to predict joint angle of human elbow in real-time. Similarly, Zhang et al. [137] proposed a linear state-space model to map the muscle activity to joint motion of elbow flexion-extension movement. Chen et al. [138] proposed a hierarchical projected regression method to predict elbow joint angles from EMG signal.

Pang et al. [139] proposed an upper limb elbow joint prediction method that uses only single-channel EMG signals. EMG signals were first recorded from the biceps muscle and a discretized recursive filter was implemented to calculate the muscle activation level. Then, they implemented a modified Hill type muscular model to predict the elbow joint angle from the muscle activation level. Tang et al. [132] estimated the elbow angle based on a backpropagation neural network to construct the EMG-angle model.

However, the simultaneous control of multiple DOFs movements is challenging. Muceli et al. [140] proposed a method to estimate wrist joint angles and hand closing based on mul-

Table 1
Some representative models and their performance in continuous motion intention prediction.

Paper	Parameter to be estimated	Model	Performance measure	Performance
[94]	Joint angle estimation	Third degree polynomial	L2-norm error values	4.34
[111]	3D arm Position	State space model	Correlation coefficient	$C_x = 0.93$, $C_y = 0.94 C_z = 0.93$
[128]	Velocity	State-space model	Correlation coefficient Root mean square error	0.965 and 0.975 0.055 rad/sec
[130]	Elbow joint	Physiological model	Root mean square error	RMSE = 6.53° (single cycle movement) RMSE = 22.4° (random cycle movement)
[132]	Elbow angle	A back-propagation neural network (BPN)	Root mean square error and Coefficient of determination	RMSE = 10.93 R2 =0.83
[133]	Angular displacement and velocity of elbow flexion/ extension	State space model with Kalman filter (EKF)	Root mean squared error Correlation coefficient	0.156 (rad/sec) and 0.142 (rad) 0.876 and 0.991
[137]	Joint motion estimation	State-space mode	Root mean square error (RMSE)	8.3%
[138]	Elbow joint angle	Hierarchical projection regression	Root mean square error	different for different loads (<13.28°)
[139]	Elbow joint	Modified Hill type muscular model	Root mean square error	<10°
[141]	Wrist flexion/extension, radial/ ulnar deviation, forearm pronation/ supination, and hand closing	Artificial neural network	Coefficient of determination	79%–88%
[141]	Shoulder abduction/adduction, shoulder flexion/extension shoulder pronation/supination and elbow flexion/extension	Artificial neural network (Multi-layer perceptron)	Coefficient of determination	87%
[142]	Shoulder movements (flexion/extension, vertical abduction/adduction, horizontal abduction/adduction) and elbow motion (flexion/extension)	Back propagation neural network (BPNN)	Mean square error	0.01615, 0.01667, 0.01897 and 0.01485
[143]	Shoulder, elbow and wrist angles	AutoRegressive with exogeneous inputs (NARX)	Variance accounted for (VAF)	> 98%

tilayer perceptron neural network. Apart from multiple DOFs, their prediction model enables users to simultaneously control hand closing. Zhang et al. [141] simultaneously predicted four joint angles across shoulder and elbow from EMG signals by using multi-layer perceptron neural network. Shoulder flexion/extension, shoulder abduction/adduction, shoulder rotation and elbow flexion/extension angles were estimated, although they did not report the performance of their prediction algorithm. Similarly, Aung et al. [142] used a back propagation neural network to estimate the shoulder and elbow joint angles from the recorded EMG signals.

Liu et al. [143] decoded shoulder, elbow, and wrist movements by using a non-linear autoregressive exogenous model. Their proposed approach is capable of simultaneously and continuously decoding multi-joint movements. Usually, developing a model to predict multiple human joint motions is complex due to the complex nature of neuromusculoskeletal systems. Mon et al. [144] estimated the angle of shoulder flexion/ extension and abduction/adduction movements by using back propagation neural network from EMG signals.

Artemiadis et al. [111] proposed a state-space model that was used to enable the user to control in real time an anthropomorphic robot arm trajectory in 3-D space. Their analysis included random arm motions in the 3-D space with variable hand speed. They were able to decode random arm motions efficiently from EMG signal. Since EMG signals are not stationary, EMG recordings for the same motion change over time. This characteristic affects the accuracy of motion prediction from the signal. However, in their work, they built a method to incorporate these signal changes into the motion decoding scheme. Table 1 shows some of the representative models and their performance in continuous motion intention prediction.

3.2. Performance measurement

The measurement of accuracy is usually used to validate the performance of a given model. However, several factors (such as computational cost) should also be considered. Computationally expensive algorithms/ models may deter the fast response of a system, which is undesired behavior, during a real-time application. The accuracy of prediction is not only dependent on the models and algorithms employed, but also on the EMG signal processing techniques, such as the number of channels and features. The accuracy of a proposed model is first measured offline for a desired performance, and we categorized such metrics as error metrics. After that, the model is tested offline and achieved a desired performance. Finally, the whole system is constructed and evaluated in real-time. We categorized such measurement as system performance metrics.

These measurement categories in EMG-based continuous motion intention prediction have different metrics. However, some of the error metrics, such as root mean square error (RMSE), can also be used in the real-time evaluation of the complete system.

3.2.1. Error metrics

Root mean square error (RMSE) is widely used as a performance measure in continuous motion prediction. It measures the average difference of the actual data points from the predicted values, and the difference is squared to avoid the cancelation of positive and negative values, while they are summed up. Mean square error (MSE) is also a similar performance measure to RMSE. However, it has a squared unit. Normalized root mean square error is another widely used performance metric in continuous motion prediction. It is a non-dimensional form of the RMSE and it is useful to compare RMSE with different units. Moreover, it can be used to compare models and algorithms of different scales. Correlation coefficient (R), which compares the strength of association between the actual and predicted values, and coefficient of determination (R^2), which is a measure of how well the prediction/ regression line represents the data, are also used. Other performance measures include L2-norm error values and variance accounted for (VAF). Table 2 shows the equation for the commonly used offline performance metrics in continuous motion prediction.

Table 2
The commonly used offline performance metrics for continuous motion estimation.

Performance Metrics	Equation of the metrics
Root mean square error (RMSE)	$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_t - y_t)^2}{n}}$ Where, y_t is the actual value at data point t, $\hat{y}_t$ is the estimated value at data point t, and n is the total number of data points.
Mean square error (MSE)	$MSE = \sum_{i=1}^{n} \frac{(\hat{y}_t - y_t)^2}{n}$ Where, y_t is the actual value at data point t, $\hat{y}_t$ is the estimated value at data point t, and n is the total number of data points.
Normalized root mean square error (NRMSE)	$NRMSE = \frac{RMSE}{y_{\max} - y_{\min}}$ Where, RMSE is root mean square error, $y_{\max}$ is the maximum of the actual value, and $y_{\min}$ is the minimum of the actual value
Correlation coefficient (R)	$R = \frac{\sum_{i=1}^{n} (x_t - \bar{x}) * (y_t - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_t - \bar{x})^2 * \sum_{i=1}^{n} (y_t - \bar{y})^2}}$ Where, y_t is the actual value at data point t, $\bar{y}$ is the mean of the actual value x_t estimated value at data point t, $\bar{x}$ is the mean of the actual value, and n is the total number of data points.

There are some limitations while validating the performance of different models/algorithms in continuous motion prediction. Most validation of the model has been conducted offline. Although there is no problem with such approaches, it cannot give the complete visualization of the system performance in real-time applications. Moreover, most studies have used healthy subjects to validate their models, whereas their system is anticipated for disabled or weak users. Some factors (e.g., arm position [145]), which affects the precision of motion estimation for healthy subjects, may not have similar effects on disabled ones. The signal intensity of healthy and disabled individuals can also be different. Therefore, a thorough analysis should be made on such factors, while inferring a system performance from healthy subject to unhealthy subjects.

3.2.2. System/task based performance metrics

Different from error metrics, system performance metrics measures the accuracy of the complete system in real-time situations. The accuracy of execution of the intended task by the system is evaluated against established metrics in the actual or simulated environment. Therefore, they are a more reliable measure. The metrics are based on Fitts's law, which is a predictive model that can be used to measure the target performance of the designed interface [146]. These performance metrics include task completion rate, task completion time, and execution efficiency [147–149]. However, RMSE can also be used in real-time prediction to measure the accuracy of trajectory. Table 3 shows the commonly used performance metrics for real-time continuous motion prediction of a system. In order to make the performance model comprehensive user comfort or satisfaction should also be evaluated.

4. Discussion and conclusion

EMG signals can be a reliable method for intention prediction of human motion in human-robot collaboration systems because they require little attention and motor skills from users and are slightly sensitive to disturbance from the environment. Moreover, they are physiologically obtained from human body so that they can establish a natural way of communication between a human and robot. The research and development of EMG-based human motion intention prediction have attracted a great deal of attention. In this paper, we focused on EMG-based continuous motion prediction from human upper limb and presented a comprehensive review of the complete systems, the models and approaches used in continuous motion estimation, the motion parameters estimated from EMG signal, and the performance metrics utilized for system validation. We reviewed the application of EMG-based human-robot collaboration systems from the perspective of both healthy and disabled users.

Many researchers have developed human-robot collaborative systems by using a continuous motion intention prediction from EMG signals of a human upper limb. However, there are several challenges associated with EMG signal acquisition, signal processing, and intention prediction to accurately and robustly predict continuous motion intention. In order to cope up with these challenges, several techniques, models, and assumptions have been proposed. However, some problems still remain to be addressed adequately to improve the performance of EMG-based motor intention prediction, develop a robust collaborative system, and expand its scope of application. In the subsequent sections, we will first discuss the challenges and then current solutions and future research directions.

4.1. Current challenges

1) *Signal acquisition devices and methods:* In the wet-electrode method of EMG signal acquisition, it is required to first clean and shave any excess hairs, and then to apply a gel to muscle position, from which the signal is collected. This procedure helps to ensure that there is a steady electrical connection between the muscle and electrode, resulting in good signal quality. However, the process requires expertise and a relatively long setup time. In addition, the comfort of the user could be impaired because many of the devices associated with this acquisition technique are bulky and several cables are attached to arms of users. Currently, there is a progress in the development of wearable devices [150,151], which are based on the dry-electrode technique. These wearable devices are comfortable to users. Also, they do not need skin preparation, resulting in the reduced setup time. However, compared to the wet-electrode technique (especially the Ag/AgCl method), the wearable EMG signal has a lower signal to noise ratio. Hence, improving signal quality is a challenge in wearable devices.

   The other challenge is that, during the real-time operation, the electrodes could shift from the target muscle or loose skin contact, which can distort the EMG signals. Besides, electrode shift from the target is one of the causes of crosstalk. As a result, there is a low quality of signals from such electrodes, which can decrease the accuracy of intention prediction from the signals.
2) *Noise and artifacts:* Noise and artifacts from several sources (including electric devices, power line, and physiological factors) affect the quality of EMG signals, which may result in a wrong interpretation of the data or inaccurate prediction of motion parameters. Even though it is difficult to acquire noise-and-artifact-free signals, it is possible to minimize the effects of noise and artifacts. Progresses have been made towards the sensors [152–154], amplifiers [155,156], filters [81], and preprocessing tools to minimize the effects. However, noise and artifacts are still a challenge in continuous motion prediction.
3) *Subject-specific and non-stationary characteristics of EMG signals:* The EMG signals vary from person to person, and even for the same person, they are different at different recording time. In addition, the change of electrode position with reference to the

Table 3
The commonly used real-time/task-based performance metrics for continuous motion estimation.

Performance metrics	Equation of the metrics	Description of the metrics
Throughput (TP)	$TP = \frac{TD}{Tc}$ Where, $TD$is the difficulty of a task, $Tc$is the completion time to acquire the target condition.	*It is defined as the ratio of the task difficulty index of each target to the completion time*
Completion rate (CR)	$CR = \frac{NCT}{NAT}$ Where,NCT is the total number of completed tasks andNAT is the total number of attempted tasks.	*It is defined as the ratio of the acquired targets (completed tasks) to the total number of attempted tasks.*
Path Efficiency (PE)	$PE = 100\% * \frac{SPD}{DT}$ WhereSPD is the shortest possible distance andDT is the distance travelled.	*It measures the control quality and is defined as the ratio of the shortest distance to the target to the travelled distance*
Speed (ν)	$\nu = \frac{TL}{Tc}$ WhereTL is the trajectory length and $Tc$is the completion time.	*It is defined as the ratio of the trajectory length to the completion time.*

active muscle fibers, the change in electrode-skin impedance, and muscle fiber lengthening and shortening impair the stationarity of EMG signals. In some cases, EMG signals are not always readily available for all users or might not be sensitive enough for interpretation (i.e., the change in the amplitude of the signals may not reflect the actual increment of muscle activity). The non-stationary characteristics of EMG signals impair the performance and robustness of motion intention prediction.

4) *Offline vs. online processing and performance evaluation:* Some EMG-based human intention prediction systems have been conducted offline and promising results are reported. However, the model or system, which has good offline performance, does not necessarily have good online performance. For instance, Jiang et al. [157] reported that there is a weak correlation between the offline and online processing performance. The other issue is that healthy subjects were used to evaluate the performance of a system that is intended for disabled users. Similarly, it is still a challenging question whether good performance of an EMG-based system for healthy users necessarily means good performance for the disabled population.
5) *Unexplored application areas:* Many EMG-based studies focus on the prediction of a single joint motion parameter under the situation of simple motion (such as reaching a target in a constrained environment). There are a few researchers, who considered random motion and multiple joints. A single joint motion parameter may be enough for rehabilitation or assistive technology because the goal can be to regain the motion of a particular joint. However, in practice, many of the daily activities from human upper limb motion involve complex motion and multiple joints. Although EMG signals can be explored for wider applications of human-robot collaboration systems, the studies on upper limb continuous motion prediction from EMG signals are centered on assistive and rehabilitation technology. Only a few studies considered how to apply human intention prediction from EMG signals to other human-robot collaboration systems (e.g, robotic manipulation [111,126]).

4.2. Possible solutions and future research directions

1) *Improving EMG signal acquisition devices and methods:* EMG signal acquisition devices, especially for real-time and commercial applications, should be simple and intuitive, portable, cheap, durable, safe, and robust. In this regard, the development in the wearable technology is promising. Since many of them are based on dry-electrode, the problem of electrode shift or lose from the target muscles needs critical investigation. The design of electrode–skin interface requires a thorough analysis of different variables involved and how they affect the acquisition of the signal. The other most important issues are noise reduction (especially power line noise) and motion artifacts of wearable devices [158]. Hence, progresses in appropriate electrodes, electronics, and signal processing for such systems are expected.

   High-density surface EMG has also evolved as a current signal acquisition method. High-density surface EMG may reduce the effect of electrode shift because it can detect almost the whole muscle skin surface. In addition, it is possible to reconstruct muscle activity maps from high-density EMG when electrode failure occurs [80,159,160], by using methods, such as image inpainting and surface reconstruction methods [79]. Signal processing approach is the other issue that needs attention. Processing techniques are used to eliminate recorded noises and artifacts from raw EMG signals. There are various pre-processing tools mainly to remove noise, such as the Bayesian filter [161], minimum entropy deconvolution [162]. Improvements and progress on processing techniques are also expected.
2) *Decomposing EMG signals to motor unit action potentials (MUAP):* EMG signals are a superposition of sequences of MUAP. Decomposition, which is the finding of MUAP from the EMG signal, provides the means to identify the neural drive to muscles and helps to understand neural control of movement. The signals recorded from both intramuscular and surface EMG can be decomposed to MUAP. However, compared to the intramuscular method, the decomposition of surface EMG signals is challenging, because of its low resolution of a signal. Since the surface EMG has the advantage of noninvasiveness, the development of appropriate algorithms and techniques to decompose EMG signals to the MUAP is valuable. In this regard, currently various techniques have been developed, such as homomorphic deconvolution [163], blind source separation methods [164–166], progressive fastICA peel-off [167], from surface EMG signals, and the progress in this direction is also expected.
3) *Fusion of EMG with other signals:* The challenges of non-stationarity and subject-specific characteristics of EMG signals could be addressed by fusing it with other signals. In this regard, fusing the signal with other signals, such as EEG [168], near-infrared spectroscopy (NIRS) [169] could enhance the performance and robustness of motion prediction and thus this research direction should be considered.
4) *Adaptive regression and improving online performance:* Improving the EMG-based system performance or robustness is critical for making EMG-based human-robot collaboration usable in real-time situations. One possible research direction is the online adaptation of the regression models to drifts in the EMG signals, considering the change of EMG signals over time and the change of muscle activity as the users develop new capabilities with experience. It is therefore important to develop a real-time learning scheme, in which both the user and machine learn simultaneously to accomplish a given task. At the same time, it is important to ensure that the proposed adaptive regression approach is computationally efficient. In this regard, there are some efforts, including the work of Hahne et al. [170]. Moreover,

to ensure the proposed system to be usable by the targeted (e.g, disabled) population, they need to be designed for and tested by the targeted population.

5) *Explore the application of EMG signal from the wider scope of human-robot collaboration systems:* Research on EMG-based rehabilitation and assistive technology has achieved many significant results. However, there are limited efforts in the other areas of EMG-based human-robot collaboration systems (such as manufacturing, intelligent vehicles, and telerobots). Further work and success of research in these areas would lead to the development of collaboration systems that can be used by the wider society, and thus improve productivity and quality of life.

Currently, there is a progress for simultaneous control of multiple DOFs based on muscle synergy motor control strategy [171–173]. To make the EMG-based motor intention prediction more practicable, multiple joints under complex motion situations should be paid significant attention. Furthermore, for wider applications, unlike rehabilitation, both the left and right arms of operators may need to move and often in different trajectories. Hence, how to use EMG signals to predict the movement intention of one arm, while the other arm is also in motion, and how to predict motion intentions of both arms at the same time, are rather useful in practice and points to a new research direction.

From the perspective of shared control, some methods have been proposed to combine the EMG and robot intelligence to improve the overall performance of collaboration systems. The shared control approaches can be used to compensate for the limitations of EMG signals. Shared control is intended to overcome some problems, such as dangerous situations and accidents, inaccuracy of human control, as well as fatigue during a continuous control over a device. Due to the lack of human control capacities, in addition to a human, intelligent controller can have an influence on a device controlled. Therefore, the development in shared control techniques and methods can also significantly improve the EMG-based human-robot collaboration systems.

Generally, since EMG signal is a potential signal for intention prediction, other areas of human-robot collaboration applications (such as human-robot collaboration for manufacturing, intelligent vehicle [174], telerobots, and skill transfer [175]) can be explored. Under the constraints of the limited and unstable performance of EMG-based systems, finding ways to enhance and ensure the overall system performance of human-robot collaboration is very important.

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References

[1] M. Ersen, E. Oztop, S. Sariel, Cognition-enabled robot manipulation in human environments: requirements, recent work, and open problems, IEEE Robot. Autom. Mag. (2017) 108–122, http://dx.doi.org/10.1109/MRA.2016.2616538.
[2] K.S. Jones, E.A. Schmidlin, Human-robot interaction: toward usable personal service robots, Rev. Hum. Factors Ergon. 7 (2011) 100–148, http://dx.doi.org/10.1177/1557234X11410388.
[3] K. Dautenhahn, Methodology & themes of human-robot interaction : a growing research field, Int. J. Adv. Robot. Syst. 4 (2007) 103–108, http://dx.doi.org/10.5772/5702.
[4] K.W. Ong, G. Seet, S.K. Sim, An implementation of seamless human- robot interaction for telerobotics, Int. J. Adv. Robot. Syst. 5 (2008) 167–176, http://dx.doi.org/10.5772/5647.
[5] N. Jarrasse, V. Sanguineti, E. Burdet, Slaves no longer : review on role assignment for human – robot joint motor action, Adapt. Behav. 22 (2014) 70–82, http://dx.doi.org/10.1177/1059712313481044.
[6] A. Mörtl, M. Lawitzky, A. Kucukyilmaz, M. Sezgin, C. Basdogan, S. Hirche, The role of roles: physical cooperation between humans and robots, Int. J. Rob. Res. 31 (2012) 1656–1674, http://dx.doi.org/10.1177/0278364912455366.
[7] S. Nikolaidis, D. Hsu, S. Srinivasa, Human-robot mutual adaptation in collaborative tasks: models and experiments, Int. J. Rob. Res. 36 (2017) 618–634, http://dx.doi.org/10.1177/0278364917690593.
[8] S. Nikolaidis, P. Lasota, G. Rossano, C. Martinez, T. Fuhlbrigge, J. Shahl, Human-robot collaboration in manufacturing : quantitative evaluation of predictable, convergent joint action, 44th Int. Symp. Robot., IEEE (2013) 1–6, http://dx.doi.org/10.1109/ISR.2013.6695625.
[9] T. Fong, J.R. Zumbado, N. Currie, A. Mishkin, D.L. Akin, Space telerobotics:unique challenges to human-robot collaboration in space, Rev. Hum. Factors Ergon. 9 (2013) 6–56, http://dx.doi.org/10.1177/1557234X13510679.
[10] K.E. Schaefer, E. Mottern, R.W. Brewer, J. Barghout, J. Putney, E.R. Straub, Relinquishing manual control: collaboration requires the capability to understand robot intent, Int. Conf. Collab. Technol. Syst., IEEE (2016) 359–366, http://dx.doi.org/10.1109/CTS.2016.69.
[11] C.J. Wong, Y.L. Tay, R. Wang, Y. Wu, Human-robot partnership : a study on collaborative storytelling, ACM/IEEE Int. Conf. Human-Robot Interact., IEEE Conference Publications (2016) 535–536, http://dx.doi.org/10.1109/HRI.2016.7451843.
[12] R. Liu, X. Zhang, Fuzzy context-specific intention inference for robotic caregiving, Int. J. Adv. Robot. Syst. 13 (2016) 1–14, http://dx.doi.org/10.1177/1729881416662780.
[13] K.E. Kaplan, K.A. Nichols, A.M. Okamura, Toward human-robot collaboration in surgery: performance assessment of human and robotic agents in an inclusion segmentation task, Int. Conf. Robot. Autom., IEEE Conference Publications (2016) 723–729, http://dx.doi.org/10.1109/ICRA.2016.7487199.
[14] C. Lenz, A. Knoll, Mechanisms and capabilities for human robot collaboration, 23rd IEEE Int. Symp. Robot Hum. Interact. Commun., IEEE (2014) 666–671, http://dx.doi.org/10.1109/ROMAN.2014.6926329.
[15] T. Carlson, Y. Demiris, Collaborative control for a robotic wheelchair: evaluation of performance, attention, and workload, IEEE Trans. Syst. Man Cybern. B Cybern. 42 (2012) 876–888, http://dx.doi.org/10.1109/TSMCB.2011.2181833.
[16] S.A. Green, M. Billinghurst, X. Chen, J.G. Chase, Human-robot collaboration: a literature review and augmented reality approach in design, Int. J. Adv. Robot. Syst. 5 (2008) 1–18, http://dx.doi.org/10.5772/5664.
[17] J. Baraglia, M. Cakmak, Y. Nagai, M. Asada, Efficient human-robot collaboration:when should a robot take initiative? Int. J. Rob. Res. 36 (2017) 563–579, http://dx.doi.org/10.1177/0278364916688253.
[18] S. Lackey, D. Barber, L. Reinerman, N.I. Badler, I. Hudson, Defining next-generation multi-modal communication in human robot interaction, Proc. Hum. Factors Ergon. Soc. Annu. Meet. 55 (2011) 461–464, http://dx.doi.org/10.1177/1071181311551095.
[19] D. Aarno, D. Kragic, Motion intention recognition in robot assisted applications, Rob. Auton. Syst. 56 (2008) 692–705, http://dx.doi.org/10.1016/j.robot.2007.11.005.
[20] K. Ramirez-amaro, M. Beetz, G. Cheng, Understanding the intention of human activities through semantic perception: observation, understanding and execution on a humanoid robot, Adv. Robot. 29 (2015) 345–362, http://dx.doi.org/10.1080/01691864.2014.1003096.
[21] S. Lemaignan, M. Warnier, E.A. Sisbot, A. Clodic, Artificial cognition for social human robot interaction : an implementation, Artif. Intell. 247 (2017) 45–69, http://dx.doi.org/10.1016/j.artint.2016.07.002.
[22] J. Mainprice, D. Berenson, human-robot collaborative manipulation planning using early prediction of human motion, Int. Conf. Intell. Robot. Syst., IEEE/RSJ (2013) 299–306, http://dx.doi.org/10.1109/IROS.2013.6696368.
[23] H. Zhou, H. Hu, Human motion tracking for rehabilitation — a survey, Biomed. Signal Process. Control 3 (2008) 1–18, http://dx.doi.org/10.1016/j.bspc.2007.09.001.
[24] A.M. Khan, F. Khan, C. Han, Estimation of desired motion intention using extreme learning machine for upper limb assist exoskeleton, IEEE Int. Conf. Adv. Intell. Mechatronics(AIM), IEEE Conference Publications (2016) 919–923, http://dx.doi.org/10.1109/AIM.2016.7576886.
[25] C. Mollaret, A.A. Mekonnen, F. Lerasle, I. Ferrané, J. Pinquier, B. Boudet, A multi-modal perception based assistive robotic system for the elderly, Comput. Vis. Image Underst. 149 (2016) 78–97, http://dx.doi.org/10.1016/j.cviu.2016.03.003.
[26] L. Peternel, N. Tsagarakis, A. Ajoudani, Towards multi-modal intention interfaces for human-robot Co-manipulation, Int. Conf. Intell. Robot. Syst., IEEE (2016) 2663–2669, http://dx.doi.org/10.1109/IROS.2016.7759414.
[27] L. Tiberio, A. Cesta, M.O. Belardinelli, Psychophysiological methods to evaluate user's response in human robot interaction: a review and feasibility study, Robotics 2 (2013) 92–121, http://dx.doi.org/10.3390/robotics2020092.
[28] A.B. Usakli, S. Gurkan, F. Aloise, G. Vecchiato, F. Babiloni, On the use of electrooculogram for efficient human computer interfaces, Comput. Intell. Neurosci. 2010 (2010) 1–5, http://dx.doi.org/10.1155/2010/135629.
[29] G. Schalk, E.C. Leuthardt, Brain-computer interfaces using electrocorticographic signals, IEEE Rev. Biomed. Eng. 4 (2011) 140–154, http://dx.doi.org/10.1109/RBME.2011.2172408.

[30] L. Bi, X.A. Fan, Y. Liu, EEG-based brain-controlled mobile robots: a survey, IEEE Trans. Human-Machine Syst. 43 (2013) 161–176, http://dx.doi.org/10.1109/TSMCC.2012.2219046.
[31] H.G. Yeom, J.S. Kim, C.K. Chung, Estimation of the velocity and trajectory of three-dimensional reaching movements from non-invasive magnetoencephalography signals, J. Neural Eng. 10 (2013), http://dx.doi.org/10.1088/1741-2560/10/2/026006.
[32] M. Hakonen, H. Piitulainen, A. Visala, Current state of digital signal processing in myoelectric interfaces and related applications, Biomed. Signal Process. Control 18 (2015) 334–359, http://dx.doi.org/10.1016/j.bspc.2015.02.009.
[33] Z. Li, C. Yang, E. Burdet, Guest editorial an overview of biomedical robotics and bio-mechatronics systems and applications, IEEE Trans. Syst. Man Cybern. Syst. 46 (2016) 869–874, http://dx.doi.org/10.1109/TSMC.2016.2571786.
[34] D. Simonetti, L. Zollo, E. Papaleo, G. Carpino, E. Guglielmelli, Multimodal adaptive interfaces for 3D robot-mediated upper limb neuro-rehabilitation : an overview of bio-cooperative systems, Rob. Auton. Syst. 85 (2016) 62–72, http://dx.doi.org/10.1016/j.robot.2016.08.012.
[35] M. Sartori, D.G. Llyod, D. Farina, Neural data-driven musculoskeletal modeling for personalized neurorehabilitation technologies, IEEE Trans. Biomed. Eng. 63 (2016) 879–893, http://dx.doi.org/10.1109/TBME.2016.2538296.
[36] C. Wong, Z. Zhang, B. Lo, G. Yang, Wearable sensing for solid biomechanics : a review, IEEE Sens. J. 15 (2015) 2747–2760, http://dx.doi.org/10.1109/JSEN.2015.2393883.
[37] M.H. Rahman, C. Ochoa-luna, M. Saad, P. Archambault, EMG based control of a robotic exoskeleton for shoulder and elbow motion assist, J. Autom. Control Eng. 3 (2015) 270–276, http://dx.doi.org/10.12720/joace.3.4.270-276.
[38] J. González, Y. Horiuchi, W. Yu, Classification of upper limb motions from around-shoulder muscle activities : hand biofeedback, Open Med. Inform. J. 4 (2010) 74–80, http://dx.doi.org/10.2174/1874431101004020074.
[39] R. Ahsan, M.I. Ibrahimy, EMG signal classification for human computer interaction : a review, Eur. J. Sci. Res. 33 (2009) 480–501, 10.1.1.468.4287.
[40] R.H. Chowdhury, M.B.I. Reaz, M. Alauddin, B. Mohd, A.A.A. Bakar, K. Chellappan, T.G. Chang, Surface electromyography signal processing and classification techniques, Sensors 13 (2013) 12431–12466, http://dx.doi.org/10.3390/s130912431.
[41] M.A. Oskoei, H. Hu, Myoelectric control systems-A survey, Biomed. Signal Process. Control 2 (2007) 275–294, http://dx.doi.org/10.1016/j.bspc.2007.07.009.
[42] P. Artemiadis, EMG-based robot control interfaces : past, present and future, Adv. Robot. Autom. 1 (2012) 10–12, http://dx.doi.org/10.4172/2168-9695.1000e107.
[43] A. Fougner, Ø. Stavdahl, P.J. Kyberd, Y.G. Losier, P.A. Parker, S. Member, Control of upper limb prostheses: terminology and proportional myoelectric control — a review, IEEE Trans. Neural Syst. Rehabil. Eng. 20 (2012) 663–677, http://dx.doi.org/10.1109/TNSRE.2012.2196711.
[44] S. Duprey, A. Naaim, F. Moissenet, M. Begon, L. Chèze, Kinematic models of the upper limb joints for multibody kinematics optimisation: an overview, J. Biomech. 62 (2017) 87–94, http://dx.doi.org/10.1016/j.jbiomech.2016.12.005.
[45] M.L. Latash, Fundamentals of Motor Control, 1st ed., Academic Press, Elsevier, MA, USA, 2012.
[46] B. Berret, E. Chiovetto, F. Nori, T. Pozzo, Evidence for composite cost functions in arm movement planning: an inverse optimal control approach, PLoS Comput. Biol. 7 (2011), http://dx.doi.org/10.1371/journal.pcbi.1002183.
[47] A. Kontaxis, A.G. Cutti, G.R. Johnson, H.E.J. Veeger, A framework for the definition of standardized protocols for measuring upper-extremity kinematics, Clin. Biomech. Bristol Avon (Bristol, Avon) 24 (2009) 246–253, http://dx.doi.org/10.1016/j.clinbiomech.2008.12.009.
[48] A. Vandenberghe, O. Levin, J. De Schutter, S. Swinnen, I. Jonkers, Three-dimensional reaching tasks: effect of reaching height and width on upper limb kinematics and muscle activity, Gait Posture 32 (2010) 500–507, http://dx.doi.org/10.1016/j.gaitpost.2010.07.009.
[49] T. Lenzi, S. Marco, M. De Rossi, N. Vitiello, M.C. Carrozza, Intention-Based EMG Control for Powered Exoskeletons, IEEE Trans. Biomed. Eng. 59 (2012) 2180–2190, http://dx.doi.org/10.1109/TBME.2012.2198821.
[50] C.L. Pulliam, J.M. Lambrecht, F.R. Kirsch, EMG-based neural network control of transhumeral prostheses, J. Rehabil. Res. Dev. 48 (2011) 739–754, http://dx.doi.org/10.1682/JRRD.2010.12.0237.
[51] A. Shafti, U.B. Lazpita, O. Elhage, H.A. Wurdemann, K. Althoefer, Analysis of comfort and ergonomics for clinical work environments, IEEE 38th Annu. Int. Conf. Eng. Med. Biol. Soc., IEEE Conference Publications (2016) 1894–1897, http://dx.doi.org/10.1109/EMBC.2016.7591091.
[52] Y. Wu, M. Ángeles, M. Martínez, P.O. Balaguer, Overview of the application of EMG recording in the diagnosis and approach of neurological disorders, Intech (2013), http://dx.doi.org/10.5772/56030.
[53] H. Türker, H. Sözen, Surface electromyography in sports and exercise, in: electrodiagnosis new front, Clin. Res., Intech Open (2013), http://dx.doi.org/10.5772/56167.
[54] C. Yih, S. Parasuraman, M.K.A.A. Khan, Electromyography (EMG) and human locomotion, Int. Symp. Robot. Intell. Sensors 2012 (IRIS 2012) (2012) 486–492, http://dx.doi.org/10.1016/j.proeng.2012.07.202.
[55] A. Ajoudani, N. Tsagarakis, A. Bicchi, Tele-impedance: teleoperation with impedance regulation using a body-machine interface, Int. J. Rob. Res. 31 (2012) 1642–1655, http://dx.doi.org/10.1177/0278364912464668.
[56] T. Lindner, C. Schulze, S. Woitge, S. Finze, W. Mittelmeier, R. Bader, The effect of the weight of equipment on muscle activity of the lower extremity in soldiers, Transfus. Apher. Sci. (2012) 1–9, http://dx.doi.org/10.1100/2012/976513.
[57] M.B.I. Reaz, M.S. Hussain, F. Mohd-Yasi, Techniques of EMG signal analysis : detection, processing, classification and applications, Biol. Proced. Online 8 (2006) 11–35, http://dx.doi.org/10.1251/bpo115.
[58] D. Staudenmann, K. Roeleveld, D.F. Stegeman, J.H. Van Dieën, Methodological aspects of SEMG recordings for force estimation – a tutorial and review, J. Electromyogr. Kinesiol. 20 (2010) 375–387, http://dx.doi.org/10.1016/j.jelekin.2009.08.005.
[59] T.A. Kuiken, M.M. Lowery, N.S. Stoykov, The effect of subcutaneous fat on myoelectric signal amplitude and cross-talk, Prosthet. Orthot. Int. 27 (2003) 48–54, http://dx.doi.org/10.3109/03093640309167976.
[60] P.K. Artemiadis, K.J. Kyriakopoulos, EMG-based control of a robot arm using low- dimensional embeddings, IEEE Trans. Robot. 26 (2010) 393–398, http://dx.doi.org/10.1109/TRO.2009.2039378.
[61] P. Geethanjali, K.K. Ray, EMG based man – machine interaction - A pattern recognition research platform, Rob. Auton. Syst. 62 (2014) 864–870, http://dx.doi.org/10.1016/j.robot.2014.01.008.
[62] E.J. Rechy-ramirez, H. Hu, Bio-signal based control in assistive robots : a survey, Digit. Commun. Networks. 1 (2015) 85–101, http://dx.doi.org/10.1016/j.dcan.2015.02.004.
[63] L.H. Smith, L.J. Hargrove, Comparison of surface and intramuscular EMG pattern recognition for simultaneous wrist/hand motion classification, Conf. Proc. IEEE Eng. Med. Biol. Soc. (2013) 4223–4226, http://dx.doi.org/10.1109/EMBC.2013.6610477.Comparison.
[64] B.S. Rajaratnam, J.C.H. Goh, V.P. Kumar, A comparison of EMG signals from surface and fine-wire electrodes during shoulder abduction, Int. J. Phys. Med. Rehabil. 2 (2014) 2–7, http://dx.doi.org/10.4172/2329-9096.1000206.
[65] E.N. Kamavuako, E.J. Scheme, K.B. Englehart, On the usability of intramuscular EMG for prosthetic control: a Fitts' Law approach, J. Electromyogr. Kinesiol. 24 (2014) 770–777, http://dx.doi.org/10.1016/j.jelekin.2014.06.009.
[66] E.N. Kamavuako, K.B. Englehart, W. Jensen, D. Farina, Simultaneous and proportional force estimation in multiple degrees of freedom from intramuscular EMG, IEEE Trans. Biomed. Eng. 59 (2012) 1804–1807, http://dx.doi.org/10.1109/TBME.2012.2197210.
[67] E.N. Kamavuako, E.J. Scheme, K.B. Englehart, Combined surface and intramuscular EMG for improved real-time myoelectric control performance, Biomed. Signal Process. Control 10 (2014) 102–107, http://dx.doi.org/10.1016/j.bspc.2014.01.007.
[68] R. Merletti, A. Botter, A. Troiano, E. Merlo, M. Alessandro, Clinical Biomechanics Technology and instrumentation for detection and conditioning of the surface electromyographic signal: State of the art, Clin. Biomech. 24 (2009) 122–134, http://dx.doi.org/10.1016/j.clinbiomech.2008.08.006.
[69] H.J. Hermens, B. Freriks, C. Disselhorst-Klug, G. Rau, Development of recommendations for SEMG sensors and sensor placement procedures, J. Electromyogr. Kinesiol. 10 (2000) 361–374, http://dx.doi.org/10.1016/S1050-6411(00)00027-4.
[70] D.A. Gabriel, Effects of monopolar and bipolar electrode configurations on surface EMG spike analysis, Med. Eng. Phys. 33 (2011) 1079–1085, http://dx.doi.org/10.1016/j.medengphy.2011.04.016.
[71] D. Staudenmann, I. Kingma, D.F. Stegeman, J.H. Van Diee, Towards optimal multi-channel EMG electrode configurations in muscle force estimation:a high density EMG study, J. Electromyogr. Kinesiol. 15 (2005) 1–11, http://dx.doi.org/10.1016/j.jelekin.2004.06.008.
[72] SENIAM project, Electrode Shape and Electrode Size (accessed November 20, 2018) http://seniam.org/.
[73] A.J. Young, L.J. Hargrove, T.A. Kuiken, The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift, IEEE Trans. Biomed. Eng. 58 (2011) 2537–2544, http://dx.doi.org/10.1109/TBME.2011.2159216.
[74] H. Ghapanchizadeh, S.A. Ahmad, A.J. Ishak, Recommended surface EMG electrode position for wrist extension and flexion, IEEE Student Symp. Biomed. Eng. Sci. Recomm. (2015) 108–112, http://dx.doi.org/10.1109/ISSBES.2015.7435877.
[75] L. Mesin, R. Merletti, A. Rainoldi, Surface EMG: the issue of electrode location, J. Electromyogr. Kinesiol. 19 (2009) 719–726, http://dx.doi.org/10.1016/j.jelekin.2008.07.006.
[76] Y. Geng, X. Zhang, Y. Zhang, G. Li, A novel channel selection method for multiple motion classification using high-density electromyography, Biomed. Eng. (NY) 13 (2014) 1–16, http://dx.doi.org/10.1186/1475-925X-13-102.
[77] E.A. Clancy, C. Martinez-luna, M. Wartenberg, C. Dai, T.R. Farrell, Two degrees of freedom quasi-static EMG-force at the wrist using a minimum number of electrodes, J. Electromyogr. Kinesiol. 34 (2017) 24–36, http://dx.doi.org/10.1016/j.jelekin.2017.03.004.
[78] J. Furukawa, T. Noda, T. Teramae, J. Morimoto, Human movement modeling to detect biosignal sensor failures for myoelectric assistive, IEEE Trans. Robot. 33 (2017) 846–857, http://dx.doi.org/10.1109/TRO.2017.2683522.

[79] P. Ghaderi, H.R. Marateb, Muscle activity map reconstruction from high density surface EMG signals with missing channels using image inpainting and surface reconstruction methods, IEEE Trans. Biomed. Eng. 64 (2017) 1513–1523, http://dx.doi.org/10.1109/TBME.2016.2603463.

[80] M. Rojas-Martínez, M.A. Mañanas, J.F. Alonso, R. Merletti, Identification of isometric contractions based on high density EMG maps, J. Electromyogr. Kinesiol. 23 (2013) 33–42, http://dx.doi.org/10.1016/j.jelekin.2012.06.009.

[81] C.J. De Luca, L.D. Gilmore, M. Kuznetsov, S.H. Roy, Filtering the surface EMG signal:movement artifact and baseline noise contamination, J. Biomech. 43 (2010) 1573–1579, http://dx.doi.org/10.1016/j.jbiomech.2010.01.027.

[82] J.M. Defreitas, T.W. Beck, M.S. Stock, Comparison of methods for removing electromagnetic noise from electromyographic signals, Physiol. Meas. 33 (2012) 147–158, http://dx.doi.org/10.1088/0967-3334/33/2/147.

[83] C.J. De Luca, M. Kuznetsov, L.D. Gilmore, S.H. Roy, Inter-electrode spacing of surface EMG sensors: reduction of crosstalk contamination during voluntary contractions, J. Biomech. 45 (2012) 555–561, http://dx.doi.org/10.1016/j.jbiomech.2011.11.010.

[84] T.S. Poo, K. Sundaraj, Design and development of a low cost EMG Signal acquisition system using surface EMG electrode, IEEE Asia Pacific Conf. Circuits Syst., IEEE (2010) 24–27, http://dx.doi.org/10.1109/APCCAS.2010.5774896.

[85] H. Li, S. Xu, P. Yang, L. Chen, A research and design on surface EMG amplifier, Int. Conf. Meas. Technol. Mechatronics Autom., IEEE (2010) 306–309, http://dx.doi.org/10.1109/ICMTMA.2010.256.

[86] R. Merletti, A. Botter, A. Troiano, E. Merlo, M. Alessandro, Clinical biomechanics technology and instrumentation for detection and conditioning of the surface electromyographic signal: State of the art, Clin. Biomech. 24 (2009) 122–134, http://dx.doi.org/10.1016/j.clinbiomech.2008.08.006.

[87] J.C. Ives, J.K. Wigglesworth, Sampling rate effects on surface EMG timing and amplitude measures, Clin. Biomech. 18 (2003) 543–552, http://dx.doi.org/10.1016/S0268-0033(03)00089-5.

[88] J.L. Durkin, J.P. Callaghan, Effects of minimum sampling rate and signal reconstruction on surface electromyographic signals, J. Electromyogr. Kinesiol. 15 (2005) 474–481, http://dx.doi.org/10.1016/j.jelekin.2005.02.003.

[89] G. Li, Y. Li, L. Yu, Y. Geng, Conditioning and sampling issues of EMG signals in motion recognition of multifunctional myoelectric prostheses, Ann. Biomed. Eng. (2011), http://dx.doi.org/10.1007/s10439-011-0265-x.

[90] M. Tomasini, S. Benatti, F. Casamassima, B. Milosevic, S. Fateh, E. Farella, L. Benini, Digitally controlled feedback for DC offset cancellation in a wearable multichannel EMG platform, 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., IEEE (2015) 3189–3192, http://dx.doi.org/10.1109/EMBC.2015.7319070.

[91] L. Frey, C. Krishnan, K. Avin, Modeling nonlinear errors in surface electromyography due to baseline noise: a new methodology, J. Biomech. 44 (2011) 202–205, http://dx.doi.org/10.1016/j.jbiomech.2010.09.008.

[92] C.J. Dakin, B.H. Dalton, B.L. Luu, J. Blouin, Rectification is required to extract oscillatory envelope modulation from surface electromyographic signals, J. Nephrol. (2014) 1685–1691, http://dx.doi.org/10.1152/jn.00296.2014.

[93] K. Koirala, M. Dasog, P. Liu, E.A. Clancy, Using the electromyogram to anticipate torques about the elbow, IEEE Trans. Neural Syst. Rehabil. Eng. 23 (2015) 396–402, http://dx.doi.org/10.1109/TNSRE.2014.2331686.

[94] R. Tibold, A.J. Fuglevand, Prediction of muscle activity during loaded movements of the upper limb, J. Neuroeng. Rehabil. 12 (2015) 1–12, http://dx.doi.org/10.1186/1743-0003-12-6.

[95] N.A. Sachs, E.A. Corbett, L.E. Miller, J. Eric, Continuous movement decoding using a target-dependent model with EMG inputs, Annu. Int. Conf. IEEE EMBS (2011) 5432–5435, http://dx.doi.org/10.1109/IEMBS.2011.6091343.

[96] H. Yu, A. Lee, Y. Choi, Human elbow joint angle estimation using electromyogram signal processing, IET Signal Process. 5 (2009) 767–775, http://dx.doi.org/10.1049/iet-spr.2009.0203.

[97] L. Pan, D. Zhang, J. Liu, X. Sheng, X. Zhu, Continuous estimation of finger joint angles under different static wrist motions from surface EMG signals, Biomed. Signal Process. Control 14 (2014) 265–271, http://dx.doi.org/10.1016/j.bspc.2014.08.004.

[98] L. Liu, P. Liu, E.A. Clancy, E. Scheme, K.B. Englehart, U.S.A. Ma, Signal whitening preprocessing for improved classification accuracies in myoelectric control, IEEE 37th Annu. Northeast Bioeng. Conf., IEEE Conference Publications (2011) 26–27, http://dx.doi.org/10.1109/NEBC.2011.5778636.

[99] C. Tapia, O. Daud, J. Ruiz-del-solar, EMG signal filtering based on independent component analysis and empirical mode decomposition for estimation of motor activation patterns, J. Med. Biol. Eng. 37 (2017) 140–155, http://dx.doi.org/10.1007/s40846-016-0201-5.

[100] Y. Li, S. Member, X. Chen, X. Zhang, ECG artifact removal from EMG recordings using independent component analysis and adapted filter *, 6th Annu. Int. IEEE EMBS Conf. Neural Eng., IEEE Conference Publications (2013) 6–8, http://dx.doi.org/10.1109/NER.2013.6695943.

[101] R.M. Howard, R. Conway, A.J. Harrison, An exploration of eliminating cross-talk in surface electromyography using independent component analysis, 26th Irish Signals Syst. Conf., IEEE Conference Publications (2015) 2–7, http://dx.doi.org/10.1109/ISSC.2015.7163754.

[102] A.O. Andrade, S. Nasuto, P. Kyberd, C.M. Sweeney-reed, F.R. Van Kanijn, EMG signal filtering based on empirical mode decomposition, Biomed. Signal Process. Control 1 (2006) 44–55, http://dx.doi.org/10.1016/j.bspc.2006.03.003.

[103] M. Naji, S.M.P. Firoozabadi, S. Kahrizi, The application of empirical Mode decomposition in elimination of ECG contamination from EMG signals, 18th Iran. Conf. Biomed. Eng., IEEE (2011) 14–16, http://dx.doi.org/10.1109/ICBME.2011.6168590.

[104] M. Dasog, K. Koirala, P. Liu, E.A. Clancy, Electromyogram bandwidth requirements when the signal is whitened, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (2014) 664–670, http://dx.doi.org/10.1109/TNSRE.2013.2283403.

[105] P. Liu, L. Liu, E.A. Clancy, S. Member, Influence of joint angle on EMG-torque model during constant-posture, torque-varying contractions, IEEE Trans. Neural Syst. Rehabil. Eng. 23 (2015) 1039–1046, http://dx.doi.org/10.1109/TNSRE.2015.2405765.

[106] H. Hayashi, A. Furui, Y. Kurita, T. Tsuji, A variance distribution model of surface EMG signals based on inverse gamma distribution, IEEE Trans. Biomed. Eng. 64 (2017) 2672–2681, http://dx.doi.org/10.1109/TBME.2017.2657121.

[107] N. Nazmi, M. Azizi, A. Rahman, S. Yamamoto, S.A. Ahmad, H. Zamzuri, S.A. Mazlan, A review of classification techniques of EMG signals during isotonic and isometric contractions, Sensors 16 (2016) 1–28, http://dx.doi.org/10.3390/s16081304.

[108] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-bernard, Y. Laurillau, EMG feature evaluation for improving myoelectric pattern recognition robustness, Expert Syst. Appl. 40 (2013) 4832–4840, http://dx.doi.org/10.1016/j.eswa.2013.02.023.

[109] A. Phinyomark, P. Phukpattaranont, C. Limsakul, Expert Systems with Applications Feature reduction and selection for EMG signal classification, Expert Syst. Appl. 39 (2012) 7420–7431, http://dx.doi.org/10.1016/j.eswa.2012.01.102.

[110] Y. Yamanoi, S. Morishita, R. Kato, H. Yokoi, Development of myoelectric hand that determines hand posture and estimates grip force simultaneously, Biomed. Signal Process. Control 38 (2017) 312–321, http://dx.doi.org/10.1016/j.bspc.2017.06.019.

[111] P.K. Artemiadis, K.J. Kyriakopoulos, An EMG-based robot control scheme robust to time-varying EMG signal features, IEEE Trans. Inf. Technol. Biomed. 14 (2010) 582–588, http://dx.doi.org/10.1109/TITB.2010.2040832.

[112] A.R. Siddiqi, S.N. Sidek, Estimation of continuous thumb angle and force using electromyogram classification, Int. J. Adv. Robot. Syst. (2016) 1–12, http://dx.doi.org/10.1177/1729881416658179.

[113] E. Nlandu, J. Celander, M. Frydensbjerg, A. Smidstrup, E. Erkocevic, M. Jörg, W. Jensen, D. Farina, Influence of the feature space on the estimation of hand grasping force from intramuscular EMG, Biomed. Signal Process. Control 8 (2013) 1–5, http://dx.doi.org/10.1016/j.bspc.2012.05.002.

[114] B.J. Borbély, P. Szolgay, Real-time inverse kinematics for the upper limb: a model- based algorithm using segment orientations, Biomed. Eng. Online 16 (2017) 1–29, http://dx.doi.org/10.1186/s12938-016-0291-x.

[115] D.L. Crouch, H. Huang, Lumped-parameter electromyogram-driven musculoskeletal hand model: a potential platform for real-time prosthesis control, J. Biomech. 49 (2016) 3901–3907, http://dx.doi.org/10.1016/j.jbiomech.2016.10.035.

[116] Y. Koike, M. Kawato, Estimation of dynamic joint torques and trajectory formation from surface electromyography signals using a neural network model, Biol. Cybern. 300 (1995) 291–300, http://dx.doi.org/10.1007/BF00199465.

[117] E.A. Clancy, L. Liu, P. Liu, D.V.Z. Moyer, Identification of constant-posture EMG – torque relationship about the elbow using nonlinear dynamic models, IEEE Trans. Biomed. Eng. 59 (2012) 205–212, http://dx.doi.org/10.1109/TBME.2011.2170423.

[118] J. Hashemi, E. Morin, P. Mousavi, K. Mountjoy, K. Hashtrudi-zaad, EMG – force modeling using parallel cascade identification, J. Electromyogr. Kinesiol. 22 (2012) 469–477, http://dx.doi.org/10.1016/j.jelekin.2011.10.012.

[119] L. Wang, T.S. Buchanan, Prediction of joint moments using a neural network model of muscle activations from EMG signals, IEEE Trans. Neural Syst. Rehabil. Eng. 10 (2002) 30–37, http://dx.doi.org/10.1109/TNSRE.2002.1021584.

[120] C. Loconsole, S. Dettori, A. Frisoli, C.A. Avizzano, M. Bergamasco, An EMG-based approach for on-line predicted torque control in robotic-assisted rehabilitation, IEEE Haptics Symp., IEEE (2014) 181–186, http://dx.doi.org/10.1109/HAPTICS.2014.6775452.

[121] J.L.G. Nielsen, S. Holmgaard, N. Jiang, K.B. Englehart, D. Farina, P.A. Parker, Simultaneous and proportional force estimation for multifunction myoelectric prostheses using mirrored bilateral training, IEEE Trans. Biomed. Eng. 58 (2011) 681–688, http://dx.doi.org/10.1109/TBME.2010.2068298.

[122] T. Teramae, T. Noda, J. Morimoto, EMG-based model predictive control for physical human- robot interaction: application for assist-as-needed control, IEEE Robot. Autom. Lett. 3 (2018) 210–217, http://dx.doi.org/10.1109/LRA.2017.2737478.

[123] K. Kiguchi, Y. Hayashi, An EMG-Based control for an upper-limb power-assist exoskeleton robot, Ieee Trans. Syst. Man Cybern. Part B 42 (2012) 1064–1071, http://dx.doi.org/10.1109/TSMCB.2012.2185843.

[124] L. Peternel, T. Noda, T. Petri, A. Ude, J. Morimoto, J. Babi, Adaptive control of exoskeleton robots for periodic assistive behaviours based on EMG feedback minimisation, PLoS One 11 (2016) 1–26, http://dx.doi.org/10.1371/journal.pone.0148942.

[125] Y. Kim, C. Park, K.G. Kim, An EMG-based variable impedance control for elbow exercise:preliminary study, Adv. Robot. 31 (2017) 1–12, http://dx.doi.org/10.1080/01691864.2017.1353440.
[126] S. Kwon, J. Kim, Real-time upper limb motion estimation from surface electromyography and joint angular velocities using an artificial neural network for human-machine cooperation, IEEE Trans. Inf. Technol. Biomed. 15 (2011) 522–530, http://dx.doi.org/10.1109/TITB.2011.2151869.
[127] P. Maciejasz, J. Eschweiler, K. Gerlach-hahn, A. Jansen-troy, S. Leonhardt, A survey on robotic devices for upper limb rehabilitation, J. OfNeuroEngineering Rehabil. 11 (2014) 1–29, http://dx.doi.org/10.1186/1743-0003-11-3.
[128] P.K. Artemiadis, K.J. Kyriakopoulos, Estimating arm motion and force using EMG signals: on the control of exoskeletons, IEEE/RSJ Int. Conf. Intell. Robot. Syst. IROS. (2008) 279–284, http://dx.doi.org/10.1109/IROS.2008.4650949.
[129] Z. Li, B. Wang, F. Sun, C. Yang, sEMG-based joint force control for an upper-limb power-assist exoskeleton robot, IEEE J. Biomed. Heal. Informatics. 18 (2014) 1043–1050, http://dx.doi.org/10.1109/JBHI.2013.2286455.
[130] J.W.L. Pau, S.S.Q. Xie, A.J. Pullan, Neuromuscular interfacing: establishing an EMG-Driven model for the human elbow joint, IEEE Trans. Biomed. Eng. 59 (2012) 2586–2593, http://dx.doi.org/10.1109/TBME.2012.2206389.
[131] A. Akhtar, N. Aghasadeghi, L. Hargrove, T. Bretl, Estimation of distal arm joint angles from EMG and shoulder orientation for transhumeral prostheses, J. Electromyogr. Kinesiol. 35 (2017) 86–94, http://dx.doi.org/10.1016/j.jelekin.2017.06.001.
[132] Z. Tang, K. Zhang, S. Sun, Z. Gao, L. Zhang, Z. Yang, An upper-limb power-assist exoskeleton using proportional myoelectric control, Sensors 14 (2014) 6677–6694, http://dx.doi.org/10.3390/s140406677.
[133] Q.C. Ding, A.B. Xiong, X.G. Zhao, J.D. Han, A novel EMG-driven State space model for the estimation of continuous joint movements, IEEE Int. Conf. Syst. Man, Cybern. (2011) 2891–2897, http://dx.doi.org/10.1109/ICSMC.2011.6084104.
[134] D. Farina, N. Jiang, H. Rehbaum, A. Holobar, B. Graimann, H. Dietl, O.C. Aszmann, The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (2014) 797–809, http://dx.doi.org/10.1109/TNSRE.2014.2305111.
[135] J. Han, Q. Ding, A. Xiong, X. Zhao, A state-space EMG model for the estimation of continuous joint movements, IEEE Trans. Ind. Electron. 62 (2015) 4267–4275, http://dx.doi.org/10.1109/TIE.2014.2387337.
[136] R. Raj, R. Rejith, K. Sivanandan, Real time identification of human forearm kinematics from surface EMG signal using artificial neural network models, Procedia Technol. 25 (2016) 44–51, http://dx.doi.org/10.1016/j.protcy.2016.08.079.
[137] Q. Zhang, R. Hosoda, G. Venture, Human joint motion estimation for electromyography (EMG) -based dynamic motion control, 35th Annu. Int. Conf. IEEE EMBS, IEEE (2013) 21–24, http://dx.doi.org/10.1109/EMBC.2013.6609427.
[138] Y. Chen, X. Zhao, J. Han, Hierarchical projection regression for online estimation of elbow joint angle using EMG signals, Neural Comput Applic. 23 (2013) 1129–1138, http://dx.doi.org/10.1007/s00521-012-1045-8.
[139] M. Pang, S. Guo, Q. Huang, H. Ishihara, Electromyography-based quantitative representation method for upper-limb elbow joint angle in sagittal plane, J. Med. Biol. Eng. 35 (2015) 165–177, http://dx.doi.org/10.1007/s40846-015-0033-8.
[140] S. Muceli, D. Farina, Simultaneous and proportional estimation of hand kinematics from EMG during mirrored movements at multiple degrees-of-Freedom, IEEE Trans. Neural Syst. Rehabil. Eng. 20 (2012) 371–378, http://dx.doi.org/10.1109/TNSRE.2011.2178039.
[141] Q. Zhang, R. Liu, W. Chen, C. Xiong, Simultaneous and continuous estimation of shoulder and elbow kinematics from surface EMG signals, Front. Neurosci. 11 (2017) 1–12, http://dx.doi.org/10.3389/fnins.2017.00280.
[142] Y.M. Aung, A. Al-jumaily, Estimation of upper limb joint angle using surface EMG signal, Int. J. Adv. Robot. Syst. 10 (2013) 1–8, http://dx.doi.org/10.5772/56717.
[143] J. Liu, S.H. Kang, D. Xu, Y. Ren, S.J. Lee, L. Zhang, EMG-based continuous and simultaneous estimation of arm kinematics in able-bodied individuals and stroke survivors, Front. Neurosci. 11 (2017) 1–11, http://dx.doi.org/10.3389/fnins.2017.00480.
[144] Y. Mon, A. Al-jumaily, sEMG based ANN for shoulder angle prediction, Int. Symp. Robot. Intell. Sensors 2012 (IRIS 2012) (2012) 1009–1015, http://dx.doi.org/10.1016/j.proeng.2012.07.276.
[145] N. Jiang, S. Muceli, B. Graimann, D. Farina, Effect of arm position on the prediction of kinematics from EMG in amputees, Med. Biol. Eng. Comput. 51 (2013) 143–151, http://dx.doi.org/10.1007/s11517-012-0979-4.
[146] J. Gusman, E. Mastinu, M. Ortiz-Catalan, Evaluation of computer-based target achievement tests for myoelectric control, IEEE J. Transl. Eng. Heal. Med. 5 (2017), http://dx.doi.org/10.1109/JTEHM.2017.2776925.
[147] R.E. Johnson, K.P. Kording, L.J. Hargrove, J.W. Sensinger, EMG versus torque control of human-machine systems: equalizing control signal variability does not equalize error or uncertainty, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (2017) 660–667, http://dx.doi.org/10.1109/TNSRE.2016.2598095.
[148] C. Choi, S. Micera, J. Carpaneto, J. Kim, Development and quantitative performance evaluation of a noninvasive EMG computer interface, IEEE Trans. Biomed. Eng. 56 (2009) 188–191, http://dx.doi.org/10.1109/TBME.2008.2005950.
[149] M. Xiloyannis, C. Gavriel, A.A.C. Thomik, A.A. Faisal, Gaussian process autoregression for simultaneous proportional multi-modal prosthetic control with natural hand kinematics, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (2017) 1785–1801, http://dx.doi.org/10.1109/TNSRE.2017.2699598.
[150] Y. Athavale, S. Krishnan, Biosignal monitoring using wearables: observations and opportunities, Biomed. Signal Process. Control 38 (2017) 22–33, http://dx.doi.org/10.1016/j.bspc.2017.03.011.
[151] A. Shafti, R.B.R. Manero, A.M. Borg, K. Althoefer, M.J. Howard, Embroidered electromyography: a systematic design guide, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (2017) 1472–1480, http://dx.doi.org/10.1109/TNSRE.2016.2633506.
[152] Y. Fukuoka, K. Miyazawa, H. Mori, M. Miyagi, M. Nishida, Y. Horiuchi, A. Ichikawa, H. Hoshino, M. Noshiro, A. Ueno, Development of a compact wireless laplacian electrode module for electromyograms and its human interface applications, Sensors. 13 (2013) 2368–2383, http://dx.doi.org/10.3390/s130202368.
[153] A. Ueno, Y. Uchikawa, M. Noshiro, A capacitive sensor system for measuring laplacian electromyogram through cloth: a pilot study, Proc. 29th Annu. Int. Conf. IEEE EMBS, IEEE (2007) 5731–5734, http://dx.doi.org/10.1109/IEMBS.2007.4353648.
[154] Dick F. Stegeman, Bert U. Kleine, Bernd G. Lapatki, JohannesP. Van Dijk, High-density surface EMG: techniques and applications at a motor unit level, Biocybern. Biomed. Eng. 32 (2012) 3–27, http://dx.doi.org/10.1016/S0208-5216(12)70039-6.
[155] D. Mrinal, A. Srivastava, J. Ananthapadmanabhan, M. Ahmad, A novel low-noise fully differential CMOS instrumentation ampli fi er with 1. 88 noise ef fi ciency factor for biomedical and sensor, Microelectronics J. 53 (2016) 35–44, http://dx.doi.org/10.1016/j.mejo.2016.04.008.
[156] K. Rendek, M. Daĝíþek, E. Vavrinský, M. Donoval, D. Donoval, Biomedical signal amplifier for EMG wireless sensor system, 8th Int. Conf. Adv. Semicond. Devices Microsystems, IEEE (2010) 8–11, http://dx.doi.org/10.1109/ASDAM.2010.5667015.
[157] N. Jiang, I. Vujaklija, H. Rehbaum, S. Member, B. Graimann, Is accurate mapping of EMG signals on kinematics needed for precise online myoelectric control? IEEE Trans. Neural Syst. Rehabil. Eng. 22 (2014) 549–558, http://dx.doi.org/10.1109/TNSRE.2013.2287383.
[158] M. Ergeneci, K. Gokcesu, E. Ertan, P. Kosmas, An embedded, eight channel, noise canceling, wireless, wearable sEMG data acquisition system, IEEE Trans. Biomed. Circuits Syst. 12 (2018) 68–79, http://dx.doi.org/10.1109/TBCAS.2017.2757400.
[159] D. Farina, T. Lorrain, F. Negro, N. Jiang, High-density EMG E-textile systems for the control of active prostheses, 2010 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBC'10 (2010) 3591–3593, http://dx.doi.org/10.1109/IEMBS.2010.5627455.
[160] S. Muceli, N. Jiang, D. Farina, Extracting signals robust to electrode number and shift for online simultaneous and proportional myoelectric control by factorization algorithms, IEEE Trans. Neural Syst. Rehabil. Eng. 22 (2014) 623–633, http://dx.doi.org/10.1109/TNSRE.2013.2282898.
[161] D. Hofmann, N. Jiang, I. Vujaklija, Bayesian filtering of surface EMG for accurate simultaneous and proportional prosthetic control, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (2016) 1333–1341, http://dx.doi.org/10.1109/TNSRE.2015.2501979.
[162] O.S. Powar, K. Chemmangat, S. Figarado, A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals, Biomed. Signal Process. Control 42 (2018) 277–286, http://dx.doi.org/10.1016/j.bspc.2018.02.006.
[163] G. Biagetti, P. Crippa, S. Orcioni, C. Turchetti, Homomorphic deconvolution for MUAP estimation from surface EMG signals, IEEE J. Biomed. Heal. INFORMATICS. 21 (2017) 328–338, http://dx.doi.org/10.1109/JBHI.2016.2530943.
[164] D. Farina, I. Vujaklija, M. Sartori, T. Kapelner, F. Negro, N. Jiang, K. Bergmeister, A. Andalib, J. Principe, O.C. Aszmann, Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation, Nat. Biomed. Eng. 1 (2017) 1–12, http://dx.doi.org/10.1038/s41551-016-0025.
[165] J. Roussel, P. Ravier, M. Haritopoulos, D. Farina, O. Buttelli, Decomposition of multi-channel intramuscular EMG signals by cyclostationary-based blind source separation, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (2017) 2035–2045, http://dx.doi.org/10.1109/TNSRE.2017.2700890.
[166] T. Kapelner, F. Negro, O.C. Aszmann, D. Farina, Decoding motor unit activity from forearm muscles: perspectives for myoelectric control, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (2018) 244–251, http://dx.doi.org/10.1109/TNSRE.2017.2766360.
[167] M. Chen, X. Zhang, X. Chen, P. Zhou, Automatic implementation of progressive FastICA peel-off for high density surface EMG decomposition, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (2018) 144–152, http://dx.doi.org/10.1109/TNSRE.2017.2759664.
[168] K. Kiguchi, Y. Hayashi, Task estimation of Upper-limb using EEG and EMG signals, IEEE/ASME Int. Conf. Adv. Intell. Mechatronics, IEEE (2014) 548–553, http://dx.doi.org/10.1109/AIM.2014.6878135.
[169] W. Guo, X. Sheng, H. Liu, X. Zhu, Toward an enhanced human – machine interface for upper-limb prosthesis control with combined, IEEE Trans. HUMAN-MACHINE Syst. (2016) 1–12, http://dx.doi.org/10.1109/THMS.2016.2641389.

[170] J.M. Hahne, S. Dähne, H. Hwang, K. Müller, L.C. Parra, Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control, IEEE Trans. Neural Syst. Rehabil. Eng. 23 (2015) 618–627, http://dx.doi.org/10.1109/TNSRE.2015.2401134.
[171] S. Zhang, X. Zhang, S. Cao, X. Gao, X. Chen, P. Zhou, Myoelectric pattern recognition based on muscle synergies for simultaneous control of dexterous finger movements, IEEE Trans. Human-Machine Syst. Tech. (2017) 1–7, http://dx.doi.org/10.1109/THMS.2017.2700444.
[172] J. Ma, N.V. Thakor, F. Matsuno, Hand and wrist movement control of myoelectric prosthesis based on synergy, IEEE Trans. Human-Machine Syst. 45 (2015) 74–83, http://dx.doi.org/10.1109/THMS.2014.2358634.
[173] M. Ison, P. Artemiadis, Proportional myoelectric control of robots: muscle synergy development drives performance enhancement, retainment, and generalization, IEEE Trans. Robot. 31 (2015) 259–268, http://dx.doi.org/10.1109/TRO.2015.2395731.
[174] G. Jang, J. Kim, S. Lee, Y. Choi, EMG-based continuous control scheme with simple classifier for electric-powered wheelchair, IEEE Trans. Ind. Electron. 63 (2016) 3695–3705, http://dx.doi.org/10.1109/TIE.2016.2522385.
[175] C. Yang, C. Zeng, P. Liang, Z. Li, R. Li, C. Su, Interface design of a physical human-robot interaction system for human impedance adaptive skill transfer, IEEE Trans. Autom. Sci. Eng. 15 (2017) 1–12, http://dx.doi.org/10.1109/TASE.2017.2743000.