Toward Robust, Adaptive and Reliable Upper-Limb Motion Estimation Using Machine Learning and Deep Learning–A Survey in Myoelectric Control

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***Abstract*—To develop multi-functional human-machine interfaces that can help disabled people reconstruct lost functions of upper-limbs, machine learning (ML) and deep learning (DL) techniques have been widely implemented to decode human movement intentions from surface electromyography (sEMG) signals. However, due to the high complexity of upper-limb movements and the inherent non-stable characteristics of sEMG, the usability of ML/DL based control schemes is still greatly limited in practical scenarios. To this end, tremendous efforts have been made to improve model robustness, adaptation, and reliability. In this article, we provide a systematic review on recent achievements, mainly from three categories: multi-modal sensing fusion to gain additional information of the user, transfer learning (TL) methods to eliminate domain shift impacts on estimation models, and post-processing approaches to obtain more reliable outcomes. Special attention is given to fusion strategies, deep TL frameworks, and confidence estimation. Research challenges and emerging opportunities, with respect to hardware development, public resources, and decoding strategies, are also analysed to provide perspectives for future developments**

***Index Terms*—Upper-limb motion estimation, myoelectric control, multi-modal fusion, transfer learning, post-processing.**

Manuscript received 22 September 2021; revised 5 January 2022 and 27 February 2022; accepted 11 March 2022. Date of publication 16 March 2022; date of current version 9 August 2022. This work was supported in part by Shandong Provincial Natural Science Foundation under Grant ZR2020KF012, in part by Engineering and Physical Sciences Research Council (EPSRC) under Grant EP/S019219/1, and in part by the School of Electronic and Electrical Engineering, University of Leeds. *(Corresponding authors: Tianzhe Bao; Zhi-Qiang Zhang.)*

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Digital Object Identifier 10.1109/JBHI.2022.3159792

I. Introduction

Characteristics of surface electromyography (sEMG) signals are highly correlated with neuromuscular activation during muscle contractions. In past decades, this property has been fully exploited in human-machine interfaces (HMI), such as intelligent prostheses, to improve the life quality of disabled people by reconstructing lost functions of upper-limbs [1]. Currently, a large number of commercial prostheses still utilise conventional control schemes such as on/off control and finite state machine [2]. Although these strategies are simple and robust, the number of degrees of freedom (DoFs) that can be actuated are very limited. This situation is evidently contrasted by the advances in mechanical design of dexterous artificial hands. Furthermore, there is usually no one-to-one relationship between muscle activities and controlled motions, and a lack of intuitiveness can increase the cognitive burden of users [3]. The limited user comfort and functionality are prone to result in the dissatisfaction of sEMG-based prosthetic devices [3]–[5].

To enable natural and multi-functional myoelectric control, machine learning (ML) approaches, i.e. classification and regression, have been widely investigated to decode user movement intentions from sEMG [6]. In particular, the classification-based control strategy, or pattern recognition (PR) scheme, aims to identify certain classes of movements by assuming that sEMG patterns can be reproducible for the same motion but separable among the different [7]. Differently, regression approaches are exploited for continuous estimation of joint kinematics/kinetics. The basic idea is that human motions follow the simultaneous and proportional control (SPC) scheme [1], thereby a coordinated task can be achieved by the co-current activation of several basic DoFs [8]. To better exploit the information of sEMG, deep learning (DL) techniques, including convolutional neural network (CNN), recurrent neural network (RNN), and auto-encoder (AE), are now gaining considerable attention in both hand gesture classification [9]–[15] and joint kinematics/kinetics regression [16]–[19]. Different from ML that relies on hand-crafted features, DL derives representative high-level features from raw signals via algorithms, which, in many cases, can be more effective.

Despite achievements of ML/DL in laboratories, estimation accuracy normally degrades substantially in practical scenarios [20]. To this end, Yang *et al.* [21] summarised confounding factors that could affect the stability of myoelectric control and reviewed the strategies aiming to improve the adaptation of classifiers among individuals and for long-term usage. Xu *et al.* [22] provided an overview on several real-life disturbances, including muscle fatigue, users difference, and electrode shift. Associated solutions were also introduced. Vincent *et al.* [23] reported recent developments in the design of prosthetic hands from four aspects: stable interfaces, advanced decoding algorithms, somatosensory feedback, and assessment methods. Apart from the above literature that focused ML applications, Phinyomark *et al.* [24] reviewed ML/DL methods for Big Data analytics in sEMG pattern recognition, mainly focusing on the comparison of feature engineering and feature learning. Xiong *et al.* [25] summarised the developments and applications of DL in both PR and SPC schemes. Meanwhile, Li *et al.* [26] reviewed the key techniques in each procedure of DL-based gesture/movement recognition.

Different from previous surveys, this paper provides a systematic review on recent progress towards model robustness, adaptation, and reliability in ML/DL based upper-limb myoelectric control. Firstly, the main factors that limit ML/DL implementations can be summarised as follows: 1) upper-limb movements are non-cyclical and have a large number of DoFs involved, whereas the information provided by sEMG signals may not be adequate enough for precise control [27], [28]; 2) characteristics of sEMG are time-varying and user-specific, in the meantime they can be easily influenced by numerous disturbances in practical environments [22]; 3) high estimation accuracy can still lead to unintended activation, causing additional operations, cognitive burdens, and even unacceptable risks [20]. In this context, related efforts will be introduced accordingly in three aspects: 1) multi-modal fusion techniques to provide additional information in myoelectric control; 2) transfer learning methods to reduce domain shift impacts on ML/DL algorithms; and 3) post-processing approaches to enhance reliability of estimation outcomes.

In this review, several databases, including Elsevier, PubMed, IEEE, SpringerLink, Google Scholar and Wiley Online Library, were used for literature search. A combination of keywords, such as sEMG, myoelectric control, classification, regression, machine learning, deep learning, robust/robustness, adaptive/adaptation, reliable/reliability, transfer learning, domain adaptation, multi-modal, sensor fusion, post-processing, confidence estimation, uncertainty analysis, etc. were used as search terms. Publications from 2010 - 2021 were preferred, but this range was extended in some cases. After literature searching, we read each paper carefully and thoroughly to exclude those that do not meet the inclusion criteria: 1) The literature must work on upper-limb motion estimation using ML/DL in myoelectric control; 2) Technical contributions well match any of the three targets, i.e. multi-modal fusion, transfer learning, and post-processing. We initially selected 106 related papers for these targets, with 46 for the first, 34 for the second, and 26 for the third, respectively.

II. ML and DL: From Feature Engineering to Feature Learning

The ML/DL based motion estimation can be formulated as a function that maps sEMG signal to target movements:

$$\widehat{\boldsymbol{y}}_t = f_{\boldsymbol{\theta}}\left(\boldsymbol{x}_t\right) \tag{1}$$

where $\boldsymbol{x}_t$ represents the t^{th} sEMG segment that is obtained by dividing a stream of sEMG signals into overlapping windows, $\widehat{\boldsymbol{y}}_t$ is the estimation result, and $f_{\boldsymbol{\theta}}(\bullet)$ denotes the algorithmic strategy. Parameters $\boldsymbol{\theta}$ can be optimised by minimising the loss function $\mathcal{L}(\boldsymbol{y}, \widehat{\boldsymbol{y}}, \boldsymbol{\theta})$ that evaluates how far the distribution of model predictions $\widehat{\boldsymbol{y}}$ is from that of measured movements $\boldsymbol{y}$.

Since sEMG signals are non-stationary and random waves, a key procedure is to obtain informative $\boldsymbol{x}_t$ to preserve the separability of sEMG patterns. In ML this target is achieved by feature engineering, where $\boldsymbol{x}_t$ is obtained by hand-crafted features, including time-domain features (TD), time-serial domain features, frequency domain features, and time-scale or time-frequency domain features [29]. To further improve the robustness of feature extraction, several new features, such as Time-Dependent Power Spectrum Descriptors (TD-PSD) [30] and Temporal-Spatial Descriptors(TSD) [31], have also been proposed recently. Since one feature can only provide limited information, it is practical to combine multi-features from different groups, such as the Hudgins' feature set [32] and the Phinyomark's feature set [29].

By contrast, DL exploits feature learning that intends to create a better representation by extracting high-level features from input data using multiple layers of processing blocks. In DL structures, both $\boldsymbol{x}_t$ and $f_{\boldsymbol{\theta}}(\bullet)$ can be learned from data simultaneously. In particular, CNN has been widely investigated to exploit the spatial information of sEMG such that the correlations of muscle groups can be fully considered. To be specific, convolution layers are applied to construct highly discriminative features of sEMG signals, which are verified to be more representative than many hand-crafted features [33], [34]. Since sEMG signals can be typically regarded as the time-series data during continuous muscle contractions, temporal dependencies of adjacent samples are also of significance. To this end, RNN and variations, including long-short term memory (LSTM) and gated recurrent units (GRU), have also been widely investigated. In this way, the contextual information of adjacent inputs can be better utilised in the recursive learning process. Different from CNN and RNN, AE is an unsupervised technique that consists of an encoder part to project sEMG features/data into a hidden vector and a decoder to regenerate these features/data. By minimising the difference between original inputs and regenerated outputs, non-linear relationships in sEMG can be captured.

III. Recent Efforts on Robust, Adaptive and Reliable Motion Estimation Using ML/DL

In this section, we will overview the recent efforts towards more robust, adaptive and reliable motion estimation using

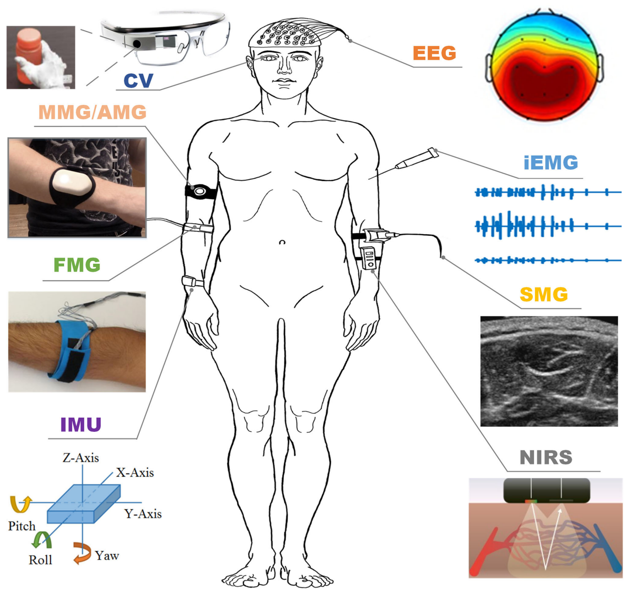

Fig. 1. The illustration of sensing modalities to be fused with sEMG in ML/DL based upper-limb motion estimation.

ML/DL in myoelectric control. As aforementioned, related efforts are categorised into three types: multi-modal sensing fusion to provide additional user information, transfer learning to enhance model generalisation/adaptability, and post-processing to reduce estimation uncertainties.

A. Multi-Modal Sensing Fusion

Despite the high correlation between sEMG and the intensity of neural drives to target muscles, sEMG signals alone may not be adequate enough for many practical applications of multi-functional upper-limb HMI, mainly because of 1) the large number of DoFs and non-cyclical nature of the upper extremity's movements [28]; 2) the complex patterns of EMG influenced by the anatomical and physiological properties of muscles, such as the limited spatial resolution caused by muscle cross-talk [27]. To this end, the fusion of sEMG with other signals have gained considerable attention, such that more complementary information can be obtained from the environment to compensate the shortcomings of sEMG. In this context, Eq. (1) can be further extended as

$$\widehat{\boldsymbol{y}}_t = f_{\boldsymbol{\theta}}\left(\boldsymbol{x}_t, \boldsymbol{s}_t\right) \tag{2}$$

where $\boldsymbol{s}_t$ denotes the physical or physiological signals to be fused with sEMG. As illustrated in Fig. 1, they mainly include mechanomyography (MMG), force myography (FMG), near-infrared spectroscopy (NIRS), ultrasound imaging or sonomyography (SMG), inertial measurement unit (IMU), electroencephalography (EEG), intramuscular EMG (iEMG), and computer vision (CV) etc.

1) MMG: MMG signals, also known as acoustic myography (AMG) when detected by microphones [35], measure the low-frequency (2-200 Hz) mechanical responses of the lateral oscillation of muscle fibre during contraction. Compared with sEMG, MMG does not suffer from the skin impedance changes and the sensitivity to sensor placement [36]. In practice, MMG can be obtained using several other types of transducers such as piezoelectric contact sensors and accelerometers [37]. Therefore, the fusion of these two signals has drawn considerable attention. Prociow *et al.* [38] developed a hybrid EMG and MMG acquisition system for hand movement recognition, and verified that the combined EMG-MMG features helped to reduce the classification error to 6.17%. Guo *et al.* [39] integrated dry EMG electrodes and a couple of accelerometers to capture two signals simultaneously. In the following study [40], the authors further compared accelerometers and microphones for MMG detection as well their effectiveness in seining fusion. Apart from those feature-based fusion strategies, a structure-level approach was also developed by Zhang *et al.* [41] to utilise MMG signals as motion onset/offset detectors for post-processing sEMG-based hand gesture recognition.

2) FMG: FMG is another mechanical counterpart of sEMG. It observes the volumetric changes of underlying musculotendinous complex or stiffness changes on the skin [42], and can be acquired via force sensing resistors (FSRs). Compared with sEMG, FMG provides a relatively stable signal against external electrical interference or sweating, and was observed to surpass sEMG in classifying wrist gestures [43]. Besides, the combined signals could reach the highest accuracy. Nowak *et al.* [44] utilised twenty sEMG and FMG sensors to simultaneously predict the opening/closing of the hand and a 2-DoFs activation of the wrist. Several combined configurations of sEMG and FMG were also explored. Ahmadizadeh *et al.* [45] investigated the feasibility of FMG as a synergist to sEMG in commercial prosthetic hands. A customised myoelectric socket was made, and two different configurations of FSRs placement were tested. To achieve the co-located EMG-FMG sensing, Jiang *et al.* [46] designed a novel armband to collect EMG and FMG simultaneously at the same muscle location, and the classification accuracy can reach 91.6±3.5%. For the recognition of finger movements, Wan *et al.* [47] suggested placing FSRs on the back of a hand to reduce the misclassification of adjacent fingers, however, the current design reduced the wearability. To enable myoelectric control for stroke survivors, Park *et al.* [48] implemented a multimodal interface that used sEMG data to decode the opening intention and the pressure sensors for hand closing.

3) NIRS: Based on the near-infrared radiation of the electromagnetic spectrum, NIRS can monitor muscle perfusion and oxygenation during contraction. For data acquisition, a LED emits near-infrared light into the tissues, and a photodetector measures the amount of light scattered nearby [49]. Therefore, NIRS can capture the state of muscles at different depths and thereby offers good spatial resolution [50], and can also compensate for the limitation of sEMG due to muscle fatigue [51]. For information fusion, Herrmann *et al.* [52] developed a customised miniature sensor composed of dry electrodes, high-intensity LEDs, and a monolithic photo amplifier integrated. The combined data were verified to provide a higher spatial resolution than each single modality, resulting in better classification of finger movements. Similarly, Attenberger *et al.* [53] observed an improved classification accuracy by fusing NIRS data with sEMG. Furthermore, Guo *et al.* [54] developed a multi-channel compact-size wireless sEMG-NIRS hybrid sensing system for prosthetic manipulation. Dry sEMG electrodes, NIRS capture components, and Bluetooth were integrated. Paleari *et al.* [50] compared three possible fusion strategies to enhance the estimation performances. A parallel strategy, in which the first classifier was trained on NIRS and the second on combined data, was mostly suggested. To further improve the wearability, Nsugbe *et al.* [51] designed a NIRS sensing armband using cheap and affordable sensors,, and managed to recognise eight discrete hand gestures with classification accuracy in the range of 79-81%.

4) SMG: SMG captures two-dimensional images of the internal body structures [55]. For measurement, an array of piezoelectric transducers is utilised to project a focused wave into the muscle, and echoes are produced when the beam interacts with tissues. During muscle contraction, different tissues produce varying qualities of echoes. Therefore, movements in both superficial and deep muscles, as well as tendons, can be inferred [56]. The combination of SMG and sEMG have also gained considerable attention. For instance, Xia *et al.* [57] developed a portable hybrid system using A-mode SMG transducer. Experiments validated that hybrid features contributed to significant improvement of hand gesture recognition (20.6% when compared to sEMG features alone). Yang *et al.* [58] explored the complementary advantages of A-mode SMG and sEMG on gesture recognition and continuous force estimation, and suggested the simultaneous combination of two sensor modalities to enhance multi-class proportional gesture control. Furthermore, experiments conducted by Boyd *et al.* [59] reaffirmed that the multimodal sensing outperformed the uni-modalities in hand motion recognition with larger arm movements, and Zeng *et al.* [60] demonstrated that the modal fusion shows better robustness against muscle fatigue, overcoming the defect of sEMG in proportional force prediction.

5) IMU: IMU combines accelerometers, gyroscopes, and magnetometers to measure the specific force, angular velocity, and orientation information of the carrier. One of the main applications of IMU in myoelectric control is to eliminate the arm position effect on hand gesture recognition. A popular strategy is to apply dual-stage classification by selecting position-specific classifiers. To be specific, the first stage serves as a position classifier based on IMU for the identification of arm positions, and the second stage works as a motion classifier trained with sEMG to recognise targeted movements [61]–[63]. Differently, in another framework both sEMG and IMU data are combined as inputs of a classifier [2], [64]–[67]. To verify the real-time performances, Krasoulis *et al.* [66] fused sEMG with 9-DoFs IMU signals in the control of a commercial prosthetic hand, resulting in significant improvement in completion rate (median increase of 25% for the able-bodied group). In the extended work, an end-to-end pipeline by using only two sEMG-IMU sensors was further proposed [2]. According to the reviewed papers, time-domain features of IMU signals (e.g. the mean value of accelerometers, gyroscopes, and magnetometers within a sliding window) were mainly exploited in sensor fusion.

6) EEG: EEG captures bio-electricity generated by the brain via electrode caps on the scalp and has several advantages over sEMG. Firstly, EEG signals are related to the mental activities of brain and thereby are much less dependent on amputation conditions. Secondly, muscle fatigue that impacts sEMG-based motion estimations will not interfere EEG-based motion estimation. Therefore, the combination of sEMG and EEG now becomes a research interest [68]–[73], where features of two signals can either be processed sequentially or simultaneously. In [69], an artificial arm for above-elbow amputees was controlled based on the parallel processing of sEMG and EEG signals, with forearm pronation/supination estimated using EEG and elbow flexion/extension decoded by sEMG. A similar study can be found in [73] to provide precise control to the prosthesis for transhumeral cases. Differently, in cascaded prediction, either sEMG signals were used as a switching mechanism to the EEG-based control or vice versa [68], [72]. For instance, in [68] EEG was firstly used to recognise the intentional voluntary movements of subjects, after which sEMG signals were used to identify the tremor onset. In [72], EEG signals acted as a gate to choose only the dedicated decoders of sEMG for estimation of the trajectory angle. In addition, the designs in [70], [71] represent another popular fusion method, in which the data of two signals were combined to enhance the estimation accuracy. The classification error can be reduced to around 5% when a DL model was exploited [71].

7) iEMG: Different from sEMG, iEMG is an invasive technique to measure EMG signals from small and deep muscles directly and selectively, providing localised information with less cross-talk. Although many researchers have observed similar estimation performances when using sEMG and iEMG individually [14], the combined EMG features (cEMG) still show potentials to improve the discrimination of upper limb movements [74], [75]. By using Fitts' Law tracking test, Kamavuako *et al.* [74] reported that the inclusion of iEMG from the deeper muscles can improve overall performances (20% improvement in Throughput was obtained with cEMG). Waris *et al.* [75] quantified the effect of time on the offline classification of hand motions with sEMG and iEMG recordings. In this study, iEMG was recorded concurrently with sEMG, with bipolar wire electrodes inserted to reside underneath each sEMG electrode pair, to measure similar activity as the sEMG. A significant difference in the between-day recognition error was observed, i.e. 7.2±7.6% for sEMG, 11.9±9.1% for iEMG, and 4.6±4.8% for cEMG. Nevertheless, the invasiveness of iEMG still greatly hinders its wearability.

8) CV: CV provides visual feedback/assistance for upper-limb myoelectric control, via local vision (e.g. a prosthetic hand embedded with cameras) [76], [77] or global vision (e.g. glasses or helmets embedded with cameras) [78], [79]. In this scenario, sEMG is usually used to interpret muscle activation for triggering prosthetic hands, whilst CV is processed to estimate the target operation and then design the moving trajectory. An early effort was firstly presented by Došen *et al.* [76], demonstrating a simple and effective fusion concept to achieve autonomous decision-making, and has been continuously optimized by following studies. For instance, Ghazaei *et al.* [77] improved the grasping ability of prosthetics by using CNN to extract grasp-related features of the low-resolution object images. Mouchoux *et al.* [78] integrated a classification-based myoelectric control with advanced scene perception provided by augmented reality (AR). The usability of the hybrid interface was successfully assessed using clinic tests. Different

TABLE I
VARIOUS SENSING MODALITIES THAT HAVE BEEN FUSED WITH sEMG IN ML/DL BASED UPPER-LIMB MOTION ESTIMATION

Modality	Measured Information	Advantages	Disadvantages		Fusion Strategies
MMG	Low-frequency mechanical responses of the lateral oscillation of muscle fibre.	1. Low sensitivity to skin impedance changes, sensor placement, and external electrical interference. 2. Good wearability in transducer size, signal processing and power consumption.	Low estimation accuracy in some tasks such as finger motion recognition	Prone to distortion from external vibrations and movement artifacts.	Feature Combination [38–40], Cascaded Prediction [41]
FMG	Volumetric changes of underlying musculo-tendinous complex.			Prone to significant drift and noise problems for both static and dynamic conditions	Feature Combination [43–47], Parallel Processing [48]
NIRS	Muscle perfusion and oxygenation.	1. Good spatial resolution by capturing the state of muscles at different depths. 2. Low sensitivity to muscle fatigue.	Sensitive to tissue thickness.		Feature Combination [50–54], Parallel Processing [50]
SMG	Morphological changes of tissues		Less sensitive to muscle force variations than sEMG		Feature Combination [57–60]
iEMG	Electrical manifestation of muscle activities (same to sEMG)	Less impacted by crosstalk due to localised placement.	Poor usability in wearable systems due to the invasive operation.		Feature Combination [74, 75]
CV	Shape, size, and position of target objects in scene perception	Visual feedback/assistance can be provided to enable semi-autonomous control.	Visual devices can be either bulky or energy-consuming.		Parallel Processing [76–79]
EEG	Electrical manifestation of brain activities.	Less dependent on amputation conditions.	Low signal-noise ratio (SNR), data transfer rate, estimation accuracy, and user adaptability.		Feature Combination [70, 71], Parallel Processing [69, 73], Cascaded Prediction [68, 72]
IMU	Orientation, velocity, and displacement of a carrier with respect to a global reference frame	1. Arm positions can be provided to promote hand motion estimation 2. Easy to be integrated into sEMG devices.	1. Unable to measure the state of muscle contractions. 2. Heavily dependent on amputation conditions.		Feature Combination [2, 64–67], Cascaded Prediction [61–63]

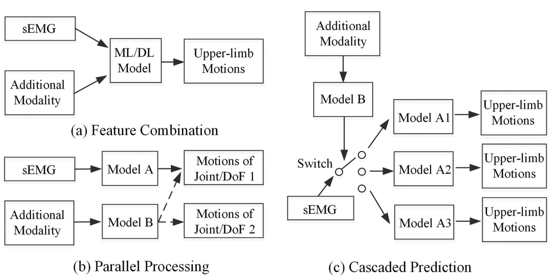

Fig. 2. Strategies to fuse sEMG and additional sensing modalities in ML/DL based upper-limb motion estimation.

from the above studies that exploited CV to activate extra DoF, Krausz *et al.* [79] used Kalman filter to fuse gaze data with sEMG for pick-and-place and observed a significant reduction of the positional error.

9) Summary: To provide complementary information for upper-limb myoelectric control, a variety of sensing modalities have been exploited. According to the searched literature, fusion strategies can be divided into three main groups: Feature Combination, Parallel Processing, and Cascaded Prediction. As illustrated in Fig. 2, Feature Combination combines features of each modality as a comprehensive input for ML/DL models. This paradigm is mostly adopted among reported literature [2], [38]–[40], [43]–[47], [50]–[54], [57]–[60], [64]–[67], [70], [71], [74], [75], attempting to improve prediction accuracy of the original model by increasing informativeness of input data. Nevertheless, it normally cannot further enhance the functionality of myoelectric systems. When applying the second strategy, sEMG and the additional modality are processed in parallel based on their specific models [48], [50], [69], [73], [76]–[79]. In this way, complicated movement intentions, such as those with multiple joints/DoFs involved, can be decoded more flexibly. To summarize, Parallel Processing predicts intentions of extra movements based on the additional modality, thereby can help to reduce user's burden or complete more challenging prosthetic operations (e.g. grasping a variety of objects, especially when users are with high-level amputation) [69], [73]. However, the sensing system and control strategy could be more complicated. As for Cascaded Prediction, the additional modality is utilized for the transition of sEMG decoding models, such that the most suitable sub-model can be selected to enhance estimation robustness against changing properties of sEMG [41], [61]–[63], [68], [72]. Apparently, Cascaded Prediction is usually designed to cope with specific scenarios/tasks, such as the elimination of arm position impact [61]–[63], and the experimental protocols can become onerous.

Table I summarises the measured information, advantages, and disadvantages of each additional modality, together with the fusion strategies. As we can see, each modality has its benefits and limitations. In specific, the information provided by iEMG, NIRS and SMG are more correlated with muscle contractions. When working as a uni-modality in motion estimation, they can achieve comparable performances than sEMG. Differently, other modalities mainly work to enrich the functionality of myoelectric control system. For example, EEG can be used to decode the brain signals and thereby is much less restricted to the amputation condition than sEMG. IMU can provide additional information on the limb orientation to benefit the robustness of sEMG models. In addition, when multiple modalities are synchronized varies among sensing systems. In general, data of MMG, FMG, IMU, iEMG, NIRS, and SMG are often integrated with sEMG during acquisition. More specifically, signals amplification, analogue-to-digital conversion, and wire/wireless transmission can be conducted concurrently via a front-end conditioning circuit. By contrast, to fuse sEMG with EEG and CV, modalities are usually collected and pre-processed by different sensing systems independently and thereafter synchronized for decoding.

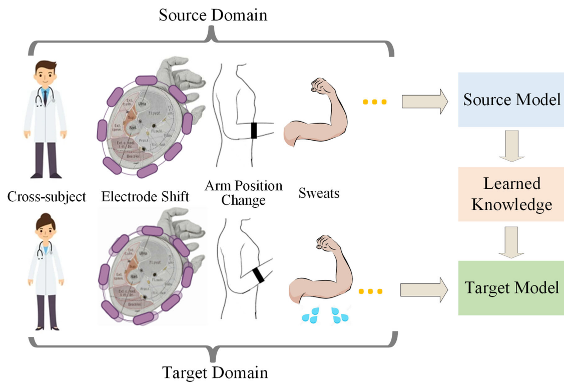

Fig. 3. Applications of TL in myoelectric control. The arm position change and electrode shift are adapted from [87] and [88].

B. Transfer Learning

Classical ML/DL assumes that training and testing data stem from the same underlying distribution [80]. However, this assumption is often violated in practical scenarios [81], which can be referred as domain shift. As a type of bio-electricity, sEMG is user-specific and even time-variant. Besides, characteristics of sEMG signals can be substantially impacted by electro-physiological changes such as muscle fatigue [82], the varying electrode-skin impedance due to perspiration or humidity [83], external/measurement factors caused by electrode shift [84], and user issues including variations of contraction intensity, hand orientations and arm positions [85]. Due to domain shift, a severe degradation usually occurs to an existing model. To this end, transfer learning (TL) approaches have been widely explored in upper-limb motion estimation. As illustrated in Fig. 3, TL utilises the knowledge learned in the source domain to promote the learning process in a target domain where sufficient labelled data are unavailable. Mathematically, given a source domain D_S and learning task T_S, while a target domain D_T and learning task T_T, TL improves $f_{\boldsymbol{\theta}}(\bullet)$ in D_T using the knowledge in D_S, where $D_S \neq D_T$ and/or $T_S \neq T_T$. As summarised by [86], when $D_S \neq D_T$ but $T_S = T_T$, TL tasks can be narrowed as domain adaptation (DA). In this context, a label-specified but domain-invariant subspace is normally extracted from the original feature spaces. Besides, a TL task $\langle D_s, T_s, D_t, T_t, f_{\boldsymbol{\theta}}(\bullet)\rangle$ is referred as conventional TL if f_θ is a traditional ML model, or deep TL when $f_{\boldsymbol{\theta}}(\bullet)$ reflects a deep neural network.

1) Conventional TL: The foundation of a positive transfer among individuals is that D_S can provide useful information for the estimation tasks in D_T. In another word, there are supposed to be inherent user-independent properties buried in sEMG signals. In this context, a preliminary study was presented by Saponas *et al.* [89], verifying that pooling data from multiple users yielded a classification result higher than chances for a novel user. This observation indicates the possibility to build cross-user algorithms. Orabona's *et al.* [90] then proposed an adaptation process to enhance the model generalisation among different users, in which the best-matched model was modified from a pool of stored datasets to fit a new subject. Chattopadhyay *et al.* [91] proposed a multi-source DA methodology based on predominantly conditional probability differences between the source and target distributions, and improved the subject independent classification accuracy by 5%. Matsubara *et al.* [92] proposed a projection approach based on a bilinear model composed of user-dependent factors and motion-dependent factors, where the latter could be further used as user-independent features for a motion classifier. More recently, Zhang *et al.* [93] introduced a dual-layer TL (dualTL) framework. The first layer leveraged correlations of sEMG among users to label target gestures, and the second layer labelled other gestures according to consistencies of sEMG between training and testing users. Jiang *et al.* [94] proposed a correlation-based data weighting (COR-W) method. The domain shift level between source and target subject was firstly evaluated via correlation alignment (CORAL), then a weighted least squares method was employed to develop a calibrated model based on previous training trials. Differently, Kanoga *et al.* [95] proposed a transfer framework to bridge source and target distributions by means of linear projection, and an ensemble strategy was exploited to ensure the positive subject-subject transfer. The classification accuracy can be increased by up to 20% after transfer. Please note that only healthy participants were recruited in the reviewed literature. In fact, it is more challenging to extract user-independent properties of sEMG among amputees since muscle activations are strictly related to the level of amputation and the kind of surgery.

As for the long-term utilisation, Sensinger *et al.* [96] compared several paradigms that employed the entropy of linear discriminant analysis (LDA) classifier for model re-training, and suggested the supervised adaptation using low-entropy samples. Liu *et al.* [97] proposed a DA algorithm for both LDA and a polynomial classifier. The new model automatically reused pre-trained models for re-learning. Following this study, Zhu *et al.* [98] further introduced a cascaded adaptation scheme including a DA component and a self-enhancing component. In the experiment, DA-based classifiers, which only used 20 new samples per class, could reach comparable accuracy (84.47% for PC and 86.72% for LDA) when compared with classifiers trained by 80 samples. Similarly, Cosima *et al.* [99] investigated a TL approach based on the generalised matrix learning vector quantization (GMLVQ) classifier, such that only a very small amount of training data was required in the following days. Benjamin *et al.* [88] presented an expectation maximisation (EM) algorithm which learned a linear transfer function between the target and source space, thereby samples in the target space could be classified correctly by the source space classifier after data mapping. By weighting the importance of training samples in the prediction of testing outputs, Vidovic *et al.* [100], Kanoga *et al.* [101], and Jung *et al.* [102] investigated the covariate shift adaptation methods to calibrate parameters of conventional classifiers such as LDA or Gaussian process regression (GPR).

2) Deep TL: Deep TL in myoelectric control can be divided into two categories: network-based approaches and feature-based approaches. Fig. 4 demonstrates the typical structures of them. In the first structure, a network is firstly trained in D_T with sufficient labelled data. Then, partial of this network is maintained by freezing the weights, and the non-frozen part is updated using either labelled or unlabelled target data. Differently, a feature-based structure attempts to

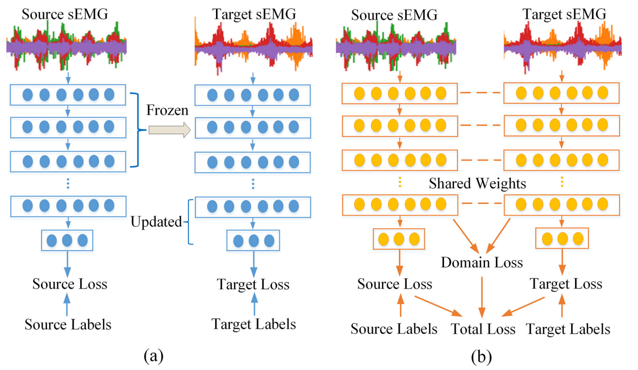

Fig. 4. The typical structures of deep TL in upper-limb myoelectric control: (a) network-based deep TL; (b) feature-based deep TL. Note that unsupervised TL can be applied when the target labels/loss are unavailable in each structure. The discussion of supervised/unsupervised TL can be found in Section III.B3.

obtain domain-invariant features via domain alignment. To be specific, front layers of the network extract features from two domains for domain loss calculation, aiming to reduce the mismatch of feature distributions in the latent space.

Fine-tuning (FT) is a simple but prevalent implementation of network-based deep TL in myoelectric control. A representative effort was presented by Wang *et al.* [67]. The authors utilised FT to enhance the training of recurrent convolutional module, where D_S data came from a public sEMG database whilst D_T was composed of multimodal data collected from experiments. Kim *et al.* [103] proposed a subject-transfer framework by fine-tuning the supportive CNN classifiers. The estimation model was examined to be more robust in terms of intra-user variability. Ameri *et al.* [104] employed FT to reduce the electrode shift impacts on CNN. Experiments in both hand gesture recognition and wrist kinematics estimation verified that FT outperformed a simple aggregation of pre-shift and post-shift sets. Recently, the generalisation of high-density sEMG matrix was also verified for both new subjects and gestures through FT [105]. In addition, Demir *et al.* [106] applied AlexNet that are pre-trained in computer vision tasks to fine-tune the sEMG images. Bird *et al.* [107] investigated FT between sEMG and EEG signals, and observed that the knowledge could be successfully transferred between two modalities. To further enhance the effectiveness of FT, Chen *et al.* [108] constructed the source gestures composed of elbow, wrist, and finger joints. They observed that even if a new gesture was not included in the source set, a good recognition accuracy could be obtained as long the activation modes of muscles were covered.

Apart from FT, several other efforts have been conducted to exploit network-based approaches. For example, Du *et al.* [10] presented a multi-stream AdaBN method to boost the inter-session performances of CNN. In the recognition phase, the adaptation process was performed by updating the statistics of batch normalisation with unlabelled calibration data. Côté-Allard *et al.* [109] applied the progressive neural networks (PNN) to decrease the training burden. The pre-training source network was firstly frozen, and a new network with random initialisation was connected with source network using merging layers. With this framework, an offline accuracy of 98.31% could be reached by CNN for 7 hand gestures and 68.98% for 18. Ketykó *et al.* [110] proposed a RNN-based two-stage framework which consists of a linear DA layer and a sequence classifier. In the adaptation stage, the classifier was frozen and DA layer was re-trained using target data. Compared with FT, a 20% improvement was reported.

As for the feature-based deep TL, weights of the network are updated by learning information from both source and target domain simultaneously, and DA is achieved by aligning feature distributions of different domains in the latent space. Inspired by the success of domain-adversarial neural networks (DANN) [111], Côté-Allard *et al.* [34] presented the adaptive DANN (ADANN) for cross-subject training. This objective was achieved by adding a domain classification head to a conventional CNN. During back-propagation, this operation learned to discriminate source and target domains via a gradient reversal process that forced the feature distributions over domains to be similar. Using a self-calibration strategy, the effectiveness of ADANN was then validated in the presence of confounding factors including inter-session and across-day variations [112]. In another following work, Campbell *et al.* [113] further tested ADANN in the cross-subject classification by requiring minimal training data from an end-user. Different from those efforts, another investigation of feature-based deep TL was presented by Bao *et al.* [114] based on a two-stream CNN with shared weights. By adding additional discrepancy losses including the maximum mean discrepancy (MMD) and a novel regression contrastive loss, distribution divergences were effectively minimised in model training.

3) Summary: In this sub-section, we mainly discussed the network structure of deep TL. As depicted by Fig. 4, TL can also be categorised as supervised TL (STL) and unsupervised TL (UTL). In STL a small amount of labelled data are present in D_T, but these data alone are insufficient to train a new model from scratch. By contrast, sufficient but unlabelled D_T data are available in UTL. For instance, FT approaches [67], [103]–[108] typically belong to STL, whilst the DANN-based approaches [34], [112], [113] exploit UTL. According to investigations on both conventional TL [96], [115] and deep TL [104], the supervised versions usually perform significantly better than unsupervised ones. Apart from a lower accuracy, another potential drawback of UTL methods is that they usually require all exemplars in D_T to be included in the calibration process, resulting in a much larger computational load than STL. Nevertheless, UTL can be of significance due to its exclusion of hardware set-up and extra time for data relabelling. In particular, during long-term usage, unlabelled data can be generated to re-train UTL models constantly [10].

C. Post-Processing

With human in the loop, user safety is critical in myoelectric control systems. However, due to the inherent variability of sEMG, a well-trained model is likely to produce unintended estimation, causing undesirable operations and even unacceptable risks to users. Therefore, several post-processing methods have been implemented to reduce potential errors of motion estimation and improve the reliability of prosthetic control. According to previous literature, the commonly used post-processing techniques can be roughly categorised into multiwindow smoothing and confidence estimation.

1) Multiwindow Smoothing: To apply ML/DL in myoelectric control, the sliding window method is normally utilised to extract sEMG signals into successive segments. Considering that adjacent windows of signals are likely to reflect the same motion, multiwindow smoothing approaches have been developed to smooth out noisy estimations. Of all related efforts, majority vote (MV) strategy is the most simple and prevalent one. It was firstly introduced by Englehart *et al.* [116] to eliminate spurious misclassification errors in the unprocessed decision stream, and has been vastly applied in hand gesture recognition tasks [117]–[120]. To summarise, MV minimises misclassification by employing successive windows of signals to make a final decision. In addition to conventional MV, some variations have also been investigated. For instance, Falk-Dahlin [121] developed three modified MV to work with the simultaneous control system. Zhai *et al.* [122] presented a MV-based label updating mechanism for CNN classifier. To increase the total number of votes for a given data stream, Wahid *et al.* [123] developed a multiwindow majority voting (MWMV) strategy composed of windows with varying lengths. Apart from implementations in non-recurrent ML/DL models, Simao *et al.* [124] applied MV for an LSTM classifier to remove the false positive results of time steps that cover the transition period between gestures.

However, MV operates on the decision stream directly without considering the actual probabilities of misclassification. By contrast, a Bayesian fusion (BF) approach was presented based on the Bayesian rule [120]. Specifically, BF utilises several posterior probabilities in a series of sliding windows to calculate the final probability of each class. The class with highest probability is selected as the final output. In addition, weighting factors are given to each sliding window, such that higher priorities are assigned for current decisions. Experiment results in [120] demonstrated that average classification accuracy of 90% across healthy subjects could be obtained, showing the superiority to MV with all number of voting decisions and across different classifiers. Competitive performances of BF over MV were also reported in amputees [125]. Another well-known method is the decision-based velocity ramp (DVR) [126]. Different from MV and BF, DVR boosts the control reliability by changing the speed of output movements. In the beginning, DVR forces a new movement to perform slowly and increases the speed when predictions of the same movement are made consecutively, with counters to track the speed of each movement. Only the movement that is currently predicted can be outputted, and the baseline speed is calculated according to muscle intensity. As reported by [126], a superiority of DVR to MV was observed, and no delay was introduced to myoelectric control since every prediction was outputted. Due to this advantage, DVR has also gained popularity in both PR scheme [127], [128] and SPC [129], [130].

In addition, post-processing approaches have also been investigated for regression since the instantaneous outputs normally contain undesirable fluctuations caused by the stochastic nature of sEMG signals. For instance, both Hahne *et al.* [131] and Hwang *et al.* [132] suggested applying an exponential

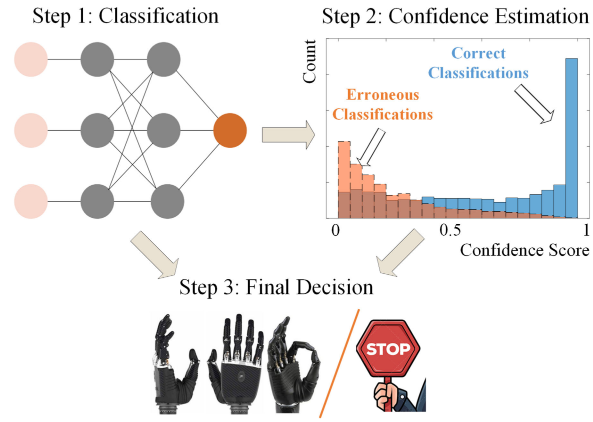

Fig. 5. A typical workflow of confidence estimation for PR-based upper-limb motion estimation. To enhance the model reliability, confidences of classification results are estimated for a rejection or smoothing operation.

moving-average filter (EMA) to smooth outputs of a LR model, considering that EMA is a simple method that reacts relatively fast without introducing a systematic overshoot in step-response. Hwang *et al.* [132] further applied a velocity control modality to filer the EMA outputs for better online performances. In this study, two online metrics, i.e., completion rate and completion time, were used to tune parameters of EMA and the velocity control. To overcome the limitation of [131] that is restricted to position control, Igual *et al.* [133] proposed an adaptive auto-regressive filter that allows for a gradual transition between position and velocity control. In this design, the additional post-processing step is never required since it is implicitly implemented in the output recursion.

2) Confidence Estimation: To enhance the usability of ML/DL, it is desirable to alleviate the negative influence of misclassification based on the analysis of model confidence. As illustrated by Fig. 5, a practical solution is to estimate the confidence of classification results, and a rejection process or smoothing operation will be further performed to cope with the unconfident/uncertain decisions. In some early efforts, Fukuda *et al.* [134], [135] suggested calculating the entropy of a log-linearised Gaussian mixture network to indicate the risk of incorrect discrimination. If the entropy exceeded a pre-specified threshold, meaning that the network output is ambiguous, the associated motor control should be suspended. This idea was further expanded by Sensinger *et al.* [96] to measure classification confidence, where entropy was calculated as a function of the probability that a feature set belonged in each class. Therefore, a decision obtained low entropy, i.e. high confidence, if only one class had a high probability.

Another representative study for confidence-based rejection was presented by Scheme *et al.* [136]. The authors linearised and normalised the log probability outputs of an LDA classifier as the confidence metric, and estimations were regarded as no-movement when the associated confidences were below a given threshold. Differently, Amsüss *et al.* [137] applied a multi-layer perceptron (MLP) to indicate the confidence of a LDA classifier and then facilitate corrections on wrong classifications using past results. In specific, LDA outputs were relabelled as +1 if they were correctly classified and −1 for erroneous ones. Meanwhile, the maximum likelihood of LDA and the mean global muscle activity of the forearm worked as features for MLP-based confidence estimation. To have a deeper perspective of confidence-based rejection, Scheme *et al.* [138] examined the confidence characteristics of several conventional classifiers and observed that low confidence was correlated with a decrease in classification accuracy. Moreover, they found that support vector machine (SVM), which allowed for more complex boundaries than other classifiers, provided a more stable rejection-to-threshold relationship during dynamic usage. Based on this finding, Robertson *et al.* [20] further investigated the range of rejection thresholds for optimal usability of SVM in real-time control. Similarly, by using a regularised discriminant analysis (RDA) classifier, Krasoulis *et al.* [2] introduced the operating characteristic (ROC) analysis for selecting class-specific confidence thresholds. In this way, the true positive rate was maximised while the false-positive rate was constrained to be smaller than a cut-off value, such that the amount of unintended performed motions could be minimised. More recently, Bao *et al.* [139] proposed an novel framework to reject uncertain classifications in CNN-based hand gesture recognition, where posterior probabilities of the softmax layer were exploited for confidence estimation. The averaged classification error in an online experiment could be reduced to 10%.

3) Summary: To post-process model predictions for more reliable control, both multiwindow smoothing and confidence estimation have been widely investigated. In specific, the former attempts to reduce the spurious estimation errors by exploiting information of consecutive sliding windows, and the latter quantifies model confidence such that uncertain estimations can be detected and suspended. In terms of multiwindow smoothing, MV and DVR are two popular methods that are used for different purposes. Nevertheless, these two methods could be applied as complements to each other. For instance, MV can work to generate a good output stream based on noisy classifications, then DVR can be utilised to convert the smoothed predictions to desirable velocities of the prosthesis. In addition, although ML/DL approaches can improve the functionality of myoelectric control, these methods suffer a lot from the lack of interpretability. In this context, confidence estimation may help to have a deeper insight into these black boxes, providing HMI with the ability to not only decide what to do but also if it should be done [138].

IV. Challenges and Opportunities

In past decades, ML/DL techniques, developed to improve the functionality and intuitiveness of myoelectric system by decoding movement intension of users, have become a substantial area of research. In addition, PR-based myoelectric control has also been successfully applied in commercial prostheses such as COAPT [140] and OttoBock [141], etc. In this survey, we particularly focus on recent efforts in multi-modal fusion, transfer learning, and post-processing, attempting to enhance the robustness, adaptation, and reliability of ML/DL performances. Nevertheless, whether state-of-the-art (SOTA) artificial intelligence (AI) techniques, especially DL, can be successfully transferred to clinic use need to be further investigated. In this section, some perspectives and thoughts on current challenges and emerging opportunities, particularly for hardware development, public resources, decoding strategies, and real-life implementation are presented.

A. Electrode Techniques

In the reviewed literature, three types of electrodes are mostly used. In brief, wet electrodes utilize conductive gel to reduce electrode-skin interface impedance and provide high-quality signal. Alternatively, dry electrodes do not need gel, thereby minimize the preparation time and increase user comfort. However, recorded data are prone to suffer from lower signal-to-noise ratio (SNR) [142]. Apart from multi-channel signals, high-density (HD) sEMG can be collected by matrix electrodes. With an increased spatio-temporal resolution of myoelectric activity, HD-sEMG is able to capture motor unit firing information (while decomposition of conventional sEMG is impractical). The motor unit behaviour can provide a novel approach for motion estimation in myoelectric control, and higher accuracy is often expected [143]. However, computational load and energy consumption are substantially increased, and experiment setup is cumbersome [144]. To summarize, sEMG acquisition via different electrodes impacts signal properties, model performances, and system complexity. A trade-off between device portability and control accuracy should be considered in real-time applications. Currently, continuous efforts are being made to advance sEMG sensors, such as tattoo ones [145] and textile ones [144], etc. providing considerable potentials to enhance the electrode-skin contact and long-term usability.

B. Open-Source Resources

To obtain sufficiently trained ML/DL models that can capture the complexity and variability of sEMG, a massive amount of information need to be learned from data. To this end, several benchmark datasets have been shared online, saving other researchers a considerable amount the time and providing effective platforms for model comparison. Representative works include Ninapro [146], CapgMyo [10], CSL-HDEMG [147], SEEDS [148], HITSIMCO [149], and Hyser [150]. Data were acquired from different experimental protocols, several types of electrodes, healthy participants and amputees, static and dynamic scenarios, and a variety of discrete gestures or continuous movements. Besides, open-source packages, such as BioPatRec [151] and Myoelectric Control Development Toolbox [152], also help to accelerate related research, with a series of techniques provided for signal pre-processing, feature engineering, motion decoding, and post-processing. However, the development of benchmarks/platforms in sEMG field is in general lagging behind other fields in biomedical engineering [24], and public resources concerning real-time experiments are still insufficient. To this end, continuous efforts are highly urged to enrich open-source resources, with more practical scenarios included, multiple sensing systems involved, and state-of-the-art decoding methods updated.

C. Neuromorphic Computing

The success of ML/DL is centred around long-term training and the use of dedicated GPU hardware. However, computational load, associated with the power consumption, can be another critical issue for the deployment of these techniques in myoelectric control [24]. Furthermore, it is desirable that the processing time can be continuously reduced to produce timely commands for actuators. To address this contradiction, researchers start to investigate neuromorphic computing which exhibits desirable properties including analogue computation, low power consumption, fast inference, event-driven processing, online learning, and massive parallelism [153]. Some primary efforts of neuromorphic computing in myoelectric control can be found in [154]–[156]. Compared with the traditional ML pipeline, the proposed system exhibited increased inference time and lower power consumption. Note that it is now possible to design mixed digital-analogue systems [154] to enable conventional ML/DL models in neuromorphic computing, the combination of two techniques can be further explored in myoelectric control.

D. Uncertainty Analysis

The black box property hinders the application of ML/DL in safety-critical areas since it is unknown to us how models make such predictions and whether they are certain about the results. In Section III.C.2, we overviewed methods that attempt to improve the control reliability based on confidence estimation of ML/DL classifiers. However, related research did not provide deep-insights on theoretical analysis. Recently, studies on model uncertainty of DL, particularly the utilisation of Bayesian approximation and ensemble learning techniques, have draw considerable attention in the DL community [157]. Further investigations have also been extended to specific applications, including autonomous driving [158], adversarial example identification [159], and robotics control [160], etc. To summarise, the potential benefits of uncertainty analysis include but are not limited to 1) knowing when to trust DL predictions, particularly under domain shift; 2) active learning via recalibration or TL when the model is uncertain; 3) better decision-making by compromising risks and gains. All these efforts can inspire further research in myoelectric control.

E. Simultaneous Control

In the past decade, PR has been extensively explored as the major approach to enhance myoelectric control. However, PR scheme identifies discrete states of movements, hence only one class could be predicted at a time [161]. In order to perform coordinated tasks, each individual function has to be selected sequentially [162], limiting the capability of dexterous manipulation over multiple DoFs and also introducing additional cognitive burden. To address this issue, numerous efforts have been made to enable simultaneous control based on PR scheme [162]–[164], mainly by adding combined motions as classification labels or exploiting a variety of sequential/parallel tropologies composed of multiple classifiers. To determine common settings for simultaneous motion classification, Camargo *et al.* [165] further investigated the feature selection for several prevalent PR algorithms, suggesting that non-linear classifiers using waveform length and entropy could achieve the best performances. It is noted that regression approaches are also being investigated to enable simultaneous control by estimating joint kinematics/kinetics, but the number of DoFs that can be reliably activated is still very limited. In this sense, the combination of classification and regression, which has been preliminarily studied by Amsuess *et al.* [166], could be a more feasible strategy.

F. Real-Life Implementation

Thus far, evaluations of ML/DL are mostly carried out using offline analysis or computer-based virtual assessment that are restricted to lab settings. Since the final target of myoelectric control is to obtain a usable device, real-life investigations on motion estimation in prosthetic control are highly desirable. Some representative works can be found in [167]–[169]. Specifically, ML-based systems were evaluated using functional tasks such as box-and-blocks test [170], clothes pin test [171], and Southampton Hand Assessment Procedure (SHAP) test [172], etc. Experimental results all indicate that ML-based myoelectric control can outperform clinically well-established approaches, e.g., co-contraction control. More recently, after monitoring a prolonged period of at-home use of a prosthetic limb worn by a participant with transhumeral amputation, Osborn *et al.* [173] reported that the effectiveness of ML-based myoelectric control could last up to one month without re-training. As for DL, Yang *et al.* [174] reported a series of robotic control, including wiping, pouring, screwing, and plugging, based on kinetics estimation using a light-weight CNN. To enhance model generalization, robustness, and adaptability, the multi-subject training strategy, data-augmentation, and fine-tuning were applied. However, those robotic tasks were completed by healthy participants, with experimental results mainly indicating the high potential of DL-based myoelectric control to be applied in industrial human-machine interaction. Therefore, the long-term usability of DL in clinic practice, i.e. the capability to promote daily activities of the disabled or amputees using prosthetics/exoskeletons, and the pros/cons of DL compared with ML, need to be further examined.

V. Conclusion

In this study, we performed a comprehensive survey of recent advances to promote myoelectric control in practical applications, mainly focusing on motion estimations using ML/DL. The similarities and differences between ML and DL in motion estimation were briefly introduced. The state-of-the-art developments of multimodal fusion, transfer learning, and post-processing were presented to provide feasible references towards model robustness, adaptation and reliability. Besides, some emerging directions including the electrode technique, neuromorphic computing, and uncertainty analysis were also introduced. Based on the above review, it can be inferred that there is a high potential for ML/DL to be transferred to both industrial application and clinic use, and the implementation of DL in wearable systems is now becoming more feasible.

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