Study on the state of the art in the field of gesture recognition

Introduction

In recent years, the concept of human-computer interaction (HCI) has been at the core of many scientific and sociological developments. Combined with the power of machine learning algorithms, it has led to some of the most outstanding achievements in nowadays technology which are used successfully in an ever-increasing number of areas impacting our lives, e.g. medicine [31], autonomous driving [43], natural language processing [83], etc. Researchers all around the world focus on providing new intuitive and accurate ways of interacting with devices around, based on gesture, voice, or vision analysis [41]. Gestures constitute a universal and intuitive way of communication, with the potential of bringing the Internet of Things (IoT) experience to a different, more organic level [66]. Automatic gesture recognition (AGR) algorithms can be successfully used in various applications, from sign language recognition (SLR) [13] to VR games [82].

Electromyography (EMG) is the process of measuring the electrical activity produced by muscles throughout the body using electrodes on the surface of the skin or inserted in the muscle [7]. Motor intent deciphered from surface EMG signals has been employed as an intuitive control strategy for dexterous multi-functional prostheses [73] and gesture recognition interfaces [70]. Myoelectric prostheses relate residual limb muscle activity to the movement of a terminal device, sometimes, by employing pattern recognition approaches to identify repeatable and distinct EMG signatures for each motion class. State-of-the-art EMG pattern recognition systems for multi-function prostheses typically contain data pre-processing, data segmentation, feature extraction, dimensionality reduction, classification, and control blocks [52]. Conceptually, this architecture can facilitate intuitive control that mimics natural neural pathways. For decades, despite substantial research and development efforts in the literature, the only real commercial application of EMG signals has been prosthetics. Recently, with the release of wearable EMG gesture control and motion control devices, such as the Myo armband in 2013, new markets have been opened. Advancements in wearable technologies have increased the potential for myoelectric devices to permeate into everyday life; however, these emerging gesture recognition interfaces suffer from similar sensitivities to many real-world factors that have been identified in the field of prosthetics [58, 64].

The real challenge for prostheses and gesture recognition interfaces are the dynamic factors that invoke changes in EMG signal characteristics. As a consequence of these factors, model inaccuracies are produced between the training phase and practical use. The common avoidance of these dynamic factors in laboratory settings creates a discrepancy between the performance of these devices in constrained settings and their reliability in regular daily use. Under ideal conditions, such as in a controlled virtual environment, the usability of multi-function prostheses has been reported to suffer when classification accuracy drops below 90% [29, 39]. While classification accuracy provides a benchmark in the laboratory, daily use invariably introduces dynamic variables not present in these conditions, leading to decreased accuracy and, ultimately, reliability of the device [27, 73]. From day to day, the reliability of previously trained models varies greatly depending on multiple factors including intra-subject repeatability, signal noise, different muscle contraction intensities and duration, limb position and forearm orientation, electrode shift, and muscle fatigue. Hands-busy conditions present additional challenges for gesture recognition tasks by introducing increased signal complexity. Furthermore, while the prostheses field has focused largely on within-user models, the widespread scaling of commercial devices for human-computer interaction would benefit from the development of multi-user classification models to eliminate the need for custom training and lengthy calibration protocols.

Gesture recognition based on EMG signals

The capacity to classify electrical responses from the muscles holds the key to creating reliable intelligent prostheses for people who have lost a limb in order to lead a normal life. Besides this utility, a system capable of classifying gestures in real time can be used to interact with various intelligent devices, *e.g.* drones, ground rover thus making the control much more intuitive and interactive [2, 6]. Even though this domain appears to have great potential and the research community is very active, reliable and affordable EMG classification techniques are not yet commercially available. This paper aims to make a further step in bringing electromyographic-based utilities to the general public. Usually, EMG classification projects do not consider designing their own acquisition module. One explanation would revolve around the added complexity that this feat would bring to the existing difficult research scheme. Another reason is the availability of EMG acquisition devices on the market. The latter is not necessarily still relevant today due to a very popular acquisition device being discontinued. For example, Myo armband, a prominent EMG signal recording module in the field [46], [30], [42], [4] is no longer available for buying [80]. Ideally, it is desired to have an entire EMG classification ecosystem with little dependency on external factors.

Pattern recognition systems, which generally consist of data pre-processing, data segmentation, feature extraction, dimensionality reduction, and classification stages (represented in Figure 1) [55], have found widespread success across many fields of biomedical engineering, including myoelectric control [73].

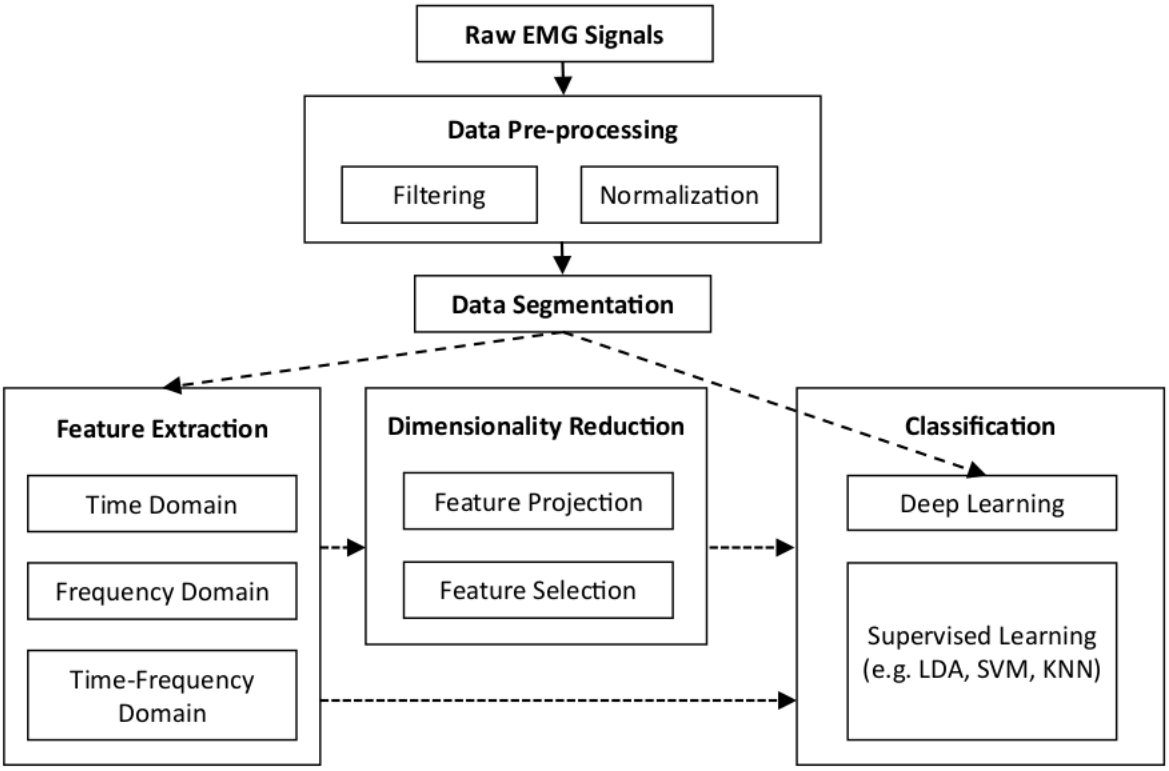

Figure 1: A structure of EMG gesture recognition systems [55]

Data pre-processing involves the strategic removal of confusing information or sources of data corruption. In EMG applications, after the raw EMG signals are prepared, a number of data pre-processing steps are applied to reduce the influence of noise, which could compromise their interpretation. Sources of noise common to EMG applications include, but are not limited to, motion artefacts, power-line interference, and electronics noise inherent in the equipment. Pre-processing steps are used to reduce the impact of these sources of corruption and prepare the input data for further analysis [14, 69].

Data segmentation involves various techniques to further prepare the pre-processed EMG signals before applying classification techniques. This step is necessary due to the fact that the stochastic EMG signals, obtained as a time series in the time-amplitude domain, are non-stationary or exhibit "non-stationarity." Many feature extraction methods assume that the data are stationary, and so the longer EMG time series is partitioned into shorter EMG segments to estimate the properties of the signal. For real-time myoelectric control systems, however, the length of these segments plus any computation must be less than 300ms to avoid noticeable delays [18]. The two main techniques for data segmentation include adjacent windowing and overlapping windowing. In adjacent windowing, contiguous and disjoint segments of a predefined length are used. More commonly, overlapping windows with window increments less than the segment length, are used to improve the density of the resulting decision stream.

Feature extraction is the process of improving the information density of the processed signals, often transforming the signals from a higher dimensional input space into a lower dimensional feature space. The selection of appropriate features has a tremendous impact on the performance of any pattern recognition system and the ideal feature set is heavily dependent on the classification task. Within the myoelectric control literature, EMG features have been commonly divided into three categories: time domain, frequency (spectral) domain, and time-scale (time-frequency) domain [57, 59, 61, 63]. The availability of high quality features that possess good class separability, minimal complexity, and are robust to dynamic factors is the most influential aspect of myoelectric control system performance [9, 85].

Dimensionality reduction is the process of either searching the computed feature space and selecting an optimal subset of high performing features (feature selection) or combining all initial features and projecting them based on some linear or non-linear mapping (feature projection) in order to maximize classification performance. Some commonly used dimensionality reduction techniques include sequential forward selection (SFS), genetic algorithms (GA), principal component analysis (PCA), and independent component analysis (ICA) [52, 56, 60].

Finally, classification involves the use of a boundary detector, or discriminant function learned through past events to estimate the class of a current event given the features presented. Substantial exploration and development of classification algorithms have been performed in myoelectric control, validating the viability of algorithms such as linear discriminant analysis (LDA), support vector machines (SVM), hidden Markov models (HMM), and artificial neural networks (ANN) [52, 60, 73].

The structure of the previous system represents a general solution, but also various approaches for AGRs, based on image or video stream analysis, leveraging on computer vision algorithms have been proposed; see for example [23, 38, 16]. Multi-modal approaches for gesture classification have been also studied [49]. Although a good performance is achieved on synthetic data, in real-life scenarios these systems may be sensitive to environmental conditions, e.g. light conditions, background, etc. Additionally, these systems are often computationally demanding and consequently not always suited for real-time applications. Because of these reasons, classical approaches that include Support Vector Machine (SVM) or Random Forest (RF) are still popular due to their simplicity. In [37] Kobylarz *et al.* tackle the problem of ternary gesture classification. Their results show that an ensemble of Random Forest and SVM achieves the best result (91.74%) in comparison to other statistical learning paradigms. Another approach is to take into account the fact that the EMG signal consists in temporal correlated data. Therefore, networks that consider time series particularities, such as Recurrent Neural Networks (RNN) are worth exploring. Simao *et al.* [75] show that although architectures such as RNN, LSTM and GRU indeed yield good results, their efficiency in terms of accuracy are similar to classical feed-forward networks (91%-95% depending on the dataset). Nonetheless, the dynamic models may still be relevant due to their less computationally expensive architecture, thus minimizing the training and inference time.

Accelerometers and electromyography (EMG) sensors provide an alternative low-cost technology for gesture sensing. The applications of sEMG-based classification systems are focused on, but not limited to, assertive devices and rehabilitation or postural control therapy for physically impaired persons [35]. With the continuous development of more versatile signal processing techniques, the applications of EMG signal classification expanded to a wide range of domains including augmented reality, gaming industry, military applications, etc.[36, 50]. Acquiring a multichannel EMG dataset may be challenging due to the constraint of always keeping the sensors in the same position with respect to the muscle groups of all participants. Also, usually all subjects must have the same upper limb position during recording

The influence of external factors on gesture recognition systems

Although classification rates of above 90% have been demonstrated in many studies, several problems must still be solved before practical and robust implementations of commercial myoelectric control systems can be realized. Consequently, four of the main challenges to deployable myoelectric control are discussed in detail in this chapter: (1) within-day and between-day variation, (2) noise, (3) variation in force, and (4) variation in limb position and forearm orientation.

The re-usability and sustainability of myoelectric control systems pose a major concern for real-world applications as devices designed for long-term use often require frequent retraining. Indeed, the requirement to retrain these devices regularly has been seen as a hindrance to the commercialization and adoption of consumer-grade myoelectric control systems. Regardless of the model performance upon creation, the non-stationarity of EMG signals (i.e., their characteristics change throughout the day, and between days) gradually degrades its performance over time (up to 20–30% [47, 53]). The source of these natural variations over time has been attributed to many factors including spatial orientation (electrode shift), electro-physiological factors (muscle fatigue, sweating, skin impedance), user intent (muscle contraction effort), and many other potential factors. Most studies make the false assumption that EMG signals are a stationary process and thus have neglected to model any temporal variations in the signal over time. A common characteristic of these studies is their short collection period (i.e., a single or few sessions in one day) within constrained laboratory settings, thus largely avoiding these signal changes.

EMG classification performance for able-bodied and amputee populations continuously degrades as the period between training and testing increases [3, 10, 32, 62, 81]. However, there is no consensus on the amount of training data sufficient for a fixed classification model to reach an asymptote in accuracy. While Waris *et. al.* [81] found a continuous decrease in performance over 7 days, a number of other studies have found that there may be periods when the classification performance is rather stable or even improves. Some have found that classification accuracy initially decreases exponentially, but then plateaus after 3 days [62], 4 days [3, 32], and 6 days [10] for able-bodied individuals, and 6–9 days for amputees [32]. A possible explanation is the subject learning effect, wherein subjects begin to elicit more repeatable gestures after becoming familiarized with the process. Because this subject learning mainly occurs during the first several days [77], training data collected after this period could reduce the need for classification algorithms to compensate for user adaptation. For example, Milosevic *et. al.* [47] found that training a classifier with data after 4 and 5 days of use provided better results for later days (testing on the 6th) than training with data from the 1st and the 2nd days of use (and testing on the 3rd day).

The majority of EMG signal processing and pattern recognition algorithms assume that the EMG data are of high quality, which can lead to invalid results or interpretations if this assumption is incorrect. It is widely acknowledged that noise contamination of EMG signals is an unavoidable problem involved in the recording data. In other words, raw EMG signals typically contain not only useful information but also some irrelevant or confounding information that adds ambiguity. The raw signal cannot, therefore be used directly, and data pre-processing is necessary to reduce the effect of noise and to improve the spectral resolution of the EMG signal. Common noise contaminants in the EMG signal can be categorized into many forms [14, 22, 45, 79], for example; (a) motion artefacts, (b) electrocardiogram (ECG) interference, (c) power line interference, (d) quantization noise, (e) analog-to-digital converter clipping, (f) amplifier saturation, (g) spurious background spikes, and (h) additive white Gaussian noise (AWGN). However, several types of noise manifest outside of the useful energy band of the EMG signal or only in a narrow specific frequency band of the signal. For instance, power line interference is clustered around 50 Hz or 60 Hz (depending on geographic location), while motion artefacts tend to be band limited in the frequency range of 0–20 Hz [69]. Use of conventional filters such as finite-impulse response (FIR) and infinite-impulse response (IIR) filters can therefore reduce these types of noise with minimal impact on the usable EMG signal [28, 17]. For example, De Luca *et. al.* [17] recommended using a Butterworth filter with a corner frequency of 20 Hz and a slope of 12 dB/oct to filter movement artefact and baseline noise contamination. Powar *et. al.* [65] used an FIR filter with coefficients that lead to the extraction of high kurtosis EMG, and that increased the classification performance by 20.5%. Adaptive digital filters, such as least mean square (LMS) and recursive least square (RLS) algorithms, have also been proposed to remove these kinds of noise [21, 51, 86].

Conventional myoelectric control schemes use an EMG amplitude estimator (such as MAV and RMS [63]) to map the intensity of the contraction of the underlying muscles to the velocity or position of a cursor or device [105]. Pattern recognition based myoelectric control, however, relies on clustering repeatable patterns of EMG activity into recognizable classes. Contractions performed at different force levels may result in drastically different features, resulting in a considerable impact on the performance of a classifier. In a study by Scheme *et. al.* [73], the ability of pattern recognition based myoelectric control to recognize human gestures in the presence of deviations in contraction intensity deviation was explored. EMG from 10 gestures was recorded at intensities ranging from 20 to 80% of maximum voluntary contraction (MVC) from 11 able-bodied subjects using an 8-channel wearable EMG armband. To test the ability of EMG pattern recognition to handle unseen force levels, the classifier was trained with each force level and then tested with each and all force levels. As expected, classification accuracy was maximized when the classifier was trained and tested with similar force levels, while the presence of contractions from unseen force levels increased the error considerably (between 32 and 44%). These results were later reiterated when Al-Timemy *et. al.* [1] investigated the effect of force variation with two transradial amputees. Similarly, their results showed that classification performance is degraded by up to 60% when the force level is varied. Importantly, the classification accuracies were found to be lower for high force levels as the amputees struggled when generating this high, and unsustainable levels [1].

The same hand and wrist gestures can also generate substantially different signal patterns when performed in different limb positions and forearm orientations, increasing classification error, and reducing robustness in real-life use [12, 20, 34, 44, 74]. It has been noted, however, that the impact of changes in limb position is less pronounced in amputees than with able-bodied subjects [25, 33]. Nevertheless, several studies have proposed three main methods to address this problem: (1) training the classifier using EMG signals recorded from different pre-defined static positions or during dynamic motion between pre-defined positions; (2) using accelerometers to measure arm positions and orientations; and (3) developing robust feature extraction, dimensionality reduction, and classification algorithms that can suppress the impact of position and orientation variations.

As with force level, a similarly successful strategy has been to inform classifier boundaries of the effect of limb positions and forearm orientations by including exemplars from each position and orientation during training [12, 20, 34, 74]. For instance, Scheme *et. al.* [74] trained an LDA classifier using EMG recorded in 8 different limb positions to discriminate eight different gestures. Within-position accuracy was found to be best with the arm hanging straight down while the position that provided the worst accuracy was when the elbow was bent at 90°. Khushaba *et. al.* [34] trained an SVM classifier using EMG recorded from 3 different forearm orientations (i.e., wrist fully supinated, at rest, and fully pronated) to discriminate six different gestures. Yang *et. al.* [84] investigated the effect of both limb positions and forearm orientations, and found that the classification performance of hand and fingers gestures are more highly impacted by forearm orientation than limb position. This result is intuitive given the proximity of extrinsic hand muscles, widely used as primary EMG sites, to the pronator and supinator muscles. Although incorporating different positions in training protocols has been shown to improve the classification accuracy, the training time and burden again limit the clinical viability of such systems [8]. Using either a dynamic motion between predefined positions or free movement of the arm in the 3-dimensional (3D) space while eliciting training gestures is therefore seen as a preferred training strategy [24, 68, 72].

Ensuring robustness in a gesture recognition system

In addition to what has already been discussed previously, two critical issues need to be addressed when developing AGR algorithms: fast enough inference to ensure real-time feeling for the end-user, and accurate and robust classification to guarantee that the gesture is correctly identified no matter the environmental conditions. Machine learning methods have become ubiquitous tools in a wide range of tasks including AGR, on account of their ability to solve a great variety of problems, from simple regressions to complex multi-modal classification.

Machine learning approaches have proven to yield results that overcome previous deterministic methods. Nevertheless, although very promising, machine learning in general and deep learning in particular need extensive datasets in order to train and offer trustworthy results [67]. Deep neural networks, which are probably the most powerful methods, may appear as black boxes whose robustness is not always well-controlled. For real-life applications, it is mandatory to guarantee the reliability of such techniques. Nowadays, the main difficulty to overcome consists in developing high-performance systems that are also trustable and safe. An additional challenge is to avoid implementation heaviness during the learning phase.

In [76], the authors showed that slightly altering data inputs that were correctly classified by the network can lead to a wrong classification [40, 11, 78]. This finding was at the origin of the concept of adversarial inputs, which constitute malicious input data that can deceive machine learning models. For example, [11] shows how voice interfaces can be fooled by creating carefully crafted artificial audio inputs of unintelligible voice that are miss-classified as specific vocal commands by the system. Also, [26] introduces several methods for generating adversarial examples on ImageNet that are so close to the original data that differences are indistinguishable for the human eye.

It must be emphasized that adversarial inputs are not necessarily artificially created with the intention to sabotage the system. As other physiological signals, e.g. EEG or EKG, EMG signals have low frequency components (usually between $10 - 150$Hz), and low amplitudes (≤ 10 mV Peak to Peak). This makes them very sensitive to noise and outside perturbations that can occur innately, under the form of noise stemming from acquisition devices, imperfect sensor contact, etc. Those can seriously flaw the performance of real-life applications based on pre-trained models [48].

In order to limit the unwanted effects introduces by adversarial attacks, as highlighted in [26], the Lipschitz behaviour of the network is tightly correlated with its robustness against adversarial attacks. The Lipschitz constant allows to upper bound the output perturbation knowing the magnitude of the input one, for a given metric [71]. Controlling this constant thus represents a feasible solution to limit the effect of adversarial attacks. Computing the exact Lipschitz constant of a neural network is however a very complex problem, so the main challenge is to find clever ways to approximate this constant effectively. Recently, several techniques to ensure the Lipschitz stability of neural networks have been explored. For example, [78] proposes a novel weight spectral normalization technique applied to stabilize the training of the discriminator in Generative Adversarial Networks (GANs). The Lipschitz constant of the network is viewed as a hyper-parameter that can be tuned in the training process of the image generation task. Doing so leads to a model with improved generalization capabilities. In [5] norm-constraint GroupSort based architectures are proposed and it is shown that they can be used as universal Lipschitz function approximators. The authors apply gradient norm preservation to create Lipschitzian networks that offer adversarial robustness guarantees. In [15] the authors introduce Parseval networks, another approach for designing networks which are intrinsically robust to adversarial noise, by imposing the Lipschitz constant of each layer of the system to be less than 1. In [19] a convex optimization framework is introduced to compute tight upper bounds for the Lipschitz constant of Deep Neural Networks (DNNs). They make use of the observation that commonly used activation operators are gradients of convex functions. Semi-definite programming approaches to ensure robustness are also explored in [54].

In conclusion, in this stage there have been reviewed and discussed several signal processing and classification techniques for myoelectric control systems. The practical considerations of how to handle the dynamic factors prevalent in real-world scenarios were emphasized. In particular, within-day and between-day variations, signal noise, variations in force, and variations in limb position and forearm orientation were highlighted, as well as methods for ensuring the robustness of the EMG gesture recognition system. Based on all these observations, it is noted that the need for a system capable of both acquiring EMG signals and processing them in an automatic way, represents an essential problem in this field. Furthermore, the hardware must be able to record data in a non-invasive way with maximum efficiency. Also, the software implementation must ensure a robustness to possible noises introduced, as well as a good performance, in order to ensure that the system provides correct results for any user.

References

[1] Ali H Al-Timemy, Guido Bugmann, Javier Escudero, and Nicholas Outram. A preliminary investigation of the effect of force variation for myoelectric control of hand prosthesis. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 5758–5761. IEEE, 2013.

[2] Cemil Altin and O Er. Designing wearable joystick and performance comparison of emg classification methods for thumb finger gestures of joystick control. *Biomed Res India*, 28:4730–4736, 2017.

[3] Sebastian Amsüss, Liliana P Paredes, Nina Rudigkeit, Bernhard Graimann, Michael J Herrmann, and Dario Farina. Long term stability of surface emg pattern classification for prosthetic control. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3622–3625. IEEE, 2013.

[4] Cristina Andronache, Marian Negru, Ana Neacsu, George Cioroiu, Anamaria Radoi, and Corneliu Burileanu. Towards extending real-time EMG-based gesture recognition system. In *2020 43rd International Conference on Telecommunications and Signal Processing (TSP)*, pages 301–304. IEEE, 2020.

[5] Cem Anil, James Lucas, and Roger Grosse. Sorting out Lipschitz function approximation. In *Proc. Int. Conf. Mach. Learn.*, pages 291–301, Long Beach, California, USA, 9–15 Jun 2019.

[6] Ray Antonius and Hendra Tjahyadi. Electromyography gesture identification using cnn-rnn neural network for controlling quadcopters. In *Journal of Physics: Conference Series*, volume 1858, page 012075. IOP Publishing, 2021.

[7] Manfredo Atzori, Arjan Gijsberts, Claudio Castellini, Barbara Caputo, Anne-Gabrielle Mittaz Hager, Simone Elsig, Giorgio Giatsidis, Franco Bassetto, and Henning Müller. Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific data*, 1(1):1–13, 2014.

[8] Joseph L Betthauser, Christopher L Hunt, Luke E Osborn, Rahul R Kaliki, and Nitish V Thakor. Limb-position robust classification of myoelectric signals for prosthesis control using sparse representations. In *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 6373–6376. IEEE, 2016.

[9] Reza Boostani and Mohammad Hassan Moradi. Evaluation of the forearm emg signal features for the control of a prosthetic hand. *Physiological measurement*, 24(2):309, 2003.

[10] Alexander Boschmann, Paul Kaufmann, Marco Platzner, and Michael Winkler. Towards multi-movement hand prostheses: Combining adaptive classification with high precision sockets. In *Proceedings of the 2nd European Conference Technically Assisted Rehabilitation*. Citeseer, 2009.

[11] Nicholas Carlini, Pratyush Mishra, Tavish Vaidya, Yuankai Zhang, Micah Sherr, Clay Shields, David Wagner, and Wenchao Zhou. Hidden voice commands. In *USENIX Security Symp.*, pages 513–530, Austin, TX, USA, 10–12 Aug 2016.

[12] Liang Chen, Yanjuan Geng, and Guanglin Li. Effect of upper-limb positions on motion pattern recognition using electromyography. In *2011 4th International Congress on Image and Signal Processing*, volume 1, pages 139–142. IEEE, 2011.

[13] Ming Jin Cheok, Zaid Omar, and Mohamed Hisham Jaward. A review of hand gesture and sign language recognition techniques. *Int. J. Mach. Learn. Cyber.*, 10(1):131–153, 2019.

[14] Rubana H Chowdhury, Mamun BI Reaz, Mohd Alauddin Bin Mohd Ali, Ashrif AA Bakar, Kalaivani Chellappan, and Tae G Chang. Surface electromyography signal processing and classification techniques. *Sensors*, 13(9):12431–12466, 2013.

[15] Moustapha Cisse, Piotr Bojanowski, Edouard Grave, Yann Dauphin, and Nicolas Usunier. Parseval networks: Improving robustness to adversarial examples. In *Proc. Int. Conf. Mach. Learn.*, pages 854–863, Sydney, NSW, Australia, 06–11 Aug 2017.

[16] Trevor J Darrell, Irfan A Essa, and Alex P Pentland. Task-specific gesture analysis in real-time using interpolated views. *IEEE Trans. Pattern Anal. Mach. Intell.*, 18(12):1236–1242, 1996.

[17] Carlo J De Luca, L Donald Gilmore, Mikhail Kuznetsov, and Serge H Roy. Filtering the surface emg signal: Movement artifact and baseline noise contamination. *Journal of biomechanics*, 43(8):1573–1579, 2010.

[18] Kevin Englehart and Bernard Hudgins. A robust, real-time control scheme for multifunction myoelectric control. *IEEE transactions on biomedical engineering*, 50(7):848–854, 2003.

[19] Mahyar Fazlyab, Alexander Robey, Hamed Hassani, Manfred Morari, and George Pappas. Efficient and accurate estimation of lipschitz constants for deep neural networks. In *Adv. Neural Info. Process. Syst.*, pages 11423–11434, Vancouver, Canada, 08–14 Dec. 2019.

[20] Anders Fougner, Erik Scheme, Adrian DC Chan, Kevin Englehart, and Øyvind Stavdahl. Resolving the limb position effect in myoelectric pattern recognition. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 19(6):644–651, 2011.

[21] Graham D Fraser, Adrian DC Chan, James R Green, N Abser, and Dawn MacIsaac. Cleanemg—power line interference estimation in semg using an adaptive least squares algorithm. In *2011 annual international conference of the IEEE engineering in medicine and biology society*, pages 7941–7944. IEEE, 2011.

[22] Graham D Fraser, Adrian DC Chan, James R Green, and Dawn T MacIsaac. Automated biosignal quality analysis for electromyography using a one-class support vector machine. *IEEE Transactions on Instrumentation and Measurement*, 63(12):2919–2930, 2014.

[23] Xiaojie Gao, Yueming Jin, Qi Dou, and Pheng-Ann Heng. Automatic gesture recognition in robot-assisted surgery with reinforcement learning and tree search. In *Proc. IEEE Int. Conf. Robot. Autom.*, pages 8440–8446, Paris, France, 31 May – 31 Aug. 2020.

[24] Marco Gazzoni, Nicolo Celadon, Davide Mastrapasqua, Marco Paleari, Valentina Margaria, and Paolo Ariano. Quantifying forearm muscle activity during wrist and finger movements by means of multi-channel electromyography. *PloS one*, 9(10):e109943, 2014.

[25] Yanjuan Geng, Ping Zhou, and Guanglin Li. Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees. *Journal of neuroengineering and rehabilitation*, 9(1):1–11, 2012.

[26] Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. In *Int. Conf. Learn. Represent.*, San Diego, CA, USA, 7–9 May 2015.

[27] Levi Hargrove, Erik Scheme, and Kevin Englehart. Myoelectric prostheses and targeted reinnervation. *Introduction to neural engineering for motor rehabilitation*, pages 291–310, 2013.

[28] Levi Hargrove, Erik Scheme, Kevin Englehart, and Bernie Hudgins. Filtering strategies for robust myoelectric pattern classification. *CMBES Proceedings*, 31, 2008.

[29] Levi J Hargrove, Erik J Scheme, Kevin B Englehart, and Bernard S Hudgins. Multiple binary classifications via linear discriminant analysis for improved controllability of a powered prosthesis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 18(1):49–57, 2010.

[30] Hussein F Hassan, Sadiq J Abou-Loukh, and Ibraheem Kasim Ibraheem. Teleoperated robotic arm movement using electromyography signal with wearable Myo armband. *Journal of King Saud University-Engineering Sciences*, 32(6):378–387, 2020.

[31] Jianxing He, Sally L Baxter, Jie Xu, Jiming Xu, Xingtao Zhou, and Kang Zhang. The practical implementation of artificial intelligence technologies in medicine. *Nat. med.*, 25(1):30–36, 2019.

[32] Jiayuan He, Dingguo Zhang, Ning Jiang, Xinjun Sheng, Dario Farina, and Xiangyang Zhu. User adaptation in long-term, open-loop myoelectric training: implications for emg pattern recognition in prosthesis control. *Journal of neural engineering*, 12(4):046005, 2015.

[33] Ning Jiang, Silvia Muceli, Bernhard Graimann, and Dario Farina. Effect of arm position on the prediction of kinematics from emg in amputees. *Medical & biological engineering & computing*, 51(1):143–151, 2013.

[34] Rami N Khushaba, Ali Al-Timemy, Sarath Kodagoda, and Kianoush Nazarpour. Combined influence of forearm orientation and muscular contraction on emg pattern recognition. *Expert Systems with Applications*, 61:154–161, 2016.

[35] Rami N Khushaba and Sarath Kodagoda. Electromyogram (EMG) feature reduction using mutual components analysis for multifunction prosthetic fingers control. In *Int. Conf. Control Autom. Robotics & Vision*, pages 1534–1539, Guangzhou, China, 5–7 Dec 2012.

[36] Jonghwa Kim, Stephan Mastnik, and Elisabeth André. EMG-based hand gesture recognition for realtime biosignal interfacing. In *Proc. Int. Conf. Intell. User Interfac.*, pages 30–39, Canaria, Spain, 13–16 Jan 2008.

[37] Jhonatan Kobylarz, Jordan J Bird, Diego R Faria, Eduardo Parente Ribeiro, and Anikó Ekárt. Thumbs up, thumbs down: Non-verbal human-robot interaction through real-time EMG classification via inductive and supervised transductive transfer learning. *Journal of Ambient Intelligence and Humanized Computing*, 11(12):6021–6031, 2020.

[38] Okan Kopuklu, Neslihan Kose, and Gerhard Rigoll. Motion fused frames: Data level fusion strategy for hand gesture recognition. In *Proc. IEEE Conf. Comput. Vis. Pattern Recogn.*, pages 2103–2111, Utah, USA, 19-22 Jun. 2018.

[39] Todd A Kuiken, Laura A Miller, Robert D Lipschutz, Blair A Lock, Kathy Stubblefield, Paul D Marasco, Ping Zhou, and Gregory A Dumanian. Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: a case study. *The Lancet*, 369(9559):371–380, 2007.

[40] Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial machine learning at scale. In *Int. Conf. Learn. Represent.*, Toulon, France, 24–26 Apr 2017.

[41] Alexey Kurakin, Zhengyou Zhang, and Zicheng Liu. A real time system for dynamic hand gesture recognition with a depth sensor. In *Proc. IEEE European Signal Processing Conf.*, pages 1975–1979, Bucharest, Romania, 27–31 Aug. 2012.

[42] Sumantri R Kurniawan and Daniel Pamungkas. MYO armband sensors and neural network algorithm for controlling hand robot. In *2018 International Conference on Applied Engineering (ICAE)*, pages 1–6. IEEE, 2018.

[43] Peiliang Li, Xiaozhi Chen, and Shaojie Shen. Stereo R-CNN based 3D object detection for autonomous driving. In *Proc. IEEE Conf. Comput. Vis. Pattern Recogn.*, pages 7644–7652, Long Beach, CA, USA, 16–20 Jun. 2019.

[44] Jianwei Liu, Dingguo Zhang, Jiayuan He, and Xiangyang Zhu. Effect of dynamic change of arm position on myoelectric pattern recognition. In *2012 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 1470–1475. IEEE, 2012.

[45] Paul McCool, Graham D Fraser, Adrian DC Chan, Lykourgos Petropoulakis, and John J Soraghan. Identification of contaminant type in surface electromyography (emg) signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(4):774–783, 2014.

[46] Irene Mendez, Bo Winther Hansen, Christine Marie Grabow, Erik Joannes Leivsgard Smedegaard, Nanna Bloch Skogberg, Xenia Jørgensen Uth, Astrid Bruhn, Bo Geng, and Ernest Nlandu Kamavuako. Evaluation of the Myo armband for the classification of hand motions. In *2017 International Conference on Rehabilitation Robotics (ICORR)*, pages 1211–1214. IEEE, 2017.

[47] Bojan Milosevic, Elisabetta Farella, and Simone Benatti. Exploring arm posture and temporal variability in myoelectric hand gesture recognition. In *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*, pages 1032–1037. IEEE, 2018.

[48] Ana Neacşu, Jean-Christophe Pesquet, and Corneliu Burileanu. Accuracy-robustness trade-off for positively weighted neural networks. In *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, pages 8389–8393, Barcelona, Spain, 4–8 May 2020.

[49] Natalia Neverova, Christian Wolf, Graham Taylor, and Florian Nebout. Moddrop: adaptive multi-modal gesture recognition. *IEEE Trans. Pattern Anal. Mach. Intell.*, 38(8):1692–1706, 2015.

[50] Alvaro David Orjuela-Cañón, Andrés F Ruíz-Olaya, and Leonardo Forero. Deep neural network for EMG signal classification of wrist position: Preliminary results. In *IEEE Latin American Conf. Comput. Intell.*, pages 1–5, Arequipa, Peru, 8–10 Nov 2017.

[51] Rodrigo Lício Ortolan, Ricardo Naoki Mori, Roberto R Pereira, Cristina MN Cabral, José Carlos Pereira, and Alberto Cliquet. Evaluation of adaptive/nonadaptive filtering and wavelet transform techniques for noise reduction in emg mobile acquisition equipment. *IEEE transactions on neural systems and rehabilitation engineering*, 11(1):60–69, 2003.

[52] Mohammadreza Asghari Oskoei and Huosheng Hu. Myoelectric control systems—a survey. *Biomedical signal processing and control*, 2(4):275–294, 2007.

[53] Francesca Palermo, Matteo Cognolato, Arjan Gijsberts, Henning Müller, Barbara Caputo, and Manfredo Atzori. Repeatability of grasp recognition for robotic hand prosthesis control based on semg data. In *2017 International Conference on Rehabilitation Robotics (ICORR)*, pages 1154–1159. IEEE, 2017.

[54] Patricia Pauli, Anne Koch, Julian Berberich, Paul Kohler, and Frank Allgower. Training robust neural networks using Lipschitz bounds. *IEEE Control Syst. Lett.*, 6:121–126, 2021.

[55] Angkoon Phinyomark, Evan Campbell, and Erik Scheme. Surface electromyography (emg) signal processing, classification, and practical considerations. In *Biomedical signal processing*, pages 3–29. Springer, 2020.

[56] Angkoon Phinyomark, Huosheng Hu, Pornchai Phukpattaranont, and Chusak Limsakul. Application of linear discriminant analysis in dimensionality reduction for hand motion classification. *Measurement Science Review*, 12(3):82–89, 2012.

[57] Angkoon Phinyomark, Chusak Limsakul, and Pornchai Phukpattaranont. Application of wavelet analysis in emg feature extraction for pattern classification. *Measurement Science Review*, 11(2):45, 2011.

[58] Angkoon Phinyomark, Rami N. Khushaba, and Erik Scheme. Feature extraction and selection for myoelectric control based on wearable emg sensors. *Sensors*, 18(5):1615, 2018.

[59] Angkoon Phinyomark, Asan Nuidod, Pornchai Phukpattaranont, and Chusak Limsakul. Feature extraction and reduction of wavelet transform coefficients for emg pattern classification. *Elektronika ir Elektrotechnika*, 122(6):27–32, 2012.

[60] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. A review of control methods for electric power wheelchairs based on electromyography signals with special emphasis on pattern recognition. *IETE Technical Review*, 28(4):316–326, 2011.

[61] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. Feature reduction and selection for emg signal classification. *Expert systems with applications*, 39(8):7420–7431, 2012.

[62] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. Investigating long-term effects of feature extraction methods for continuous emg pattern classification. *Fluctuation and Noise Letters*, 11(04):1250028, 2012.

[63] Angkoon Phinyomark, Franck Quaine, Sylvie Charbonnier, Christine Serviere, Franck Tarpin-Bernard, and Yann Laurillau. Emg feature evaluation for improving myoelectric pattern recognition robustness. *Expert Systems with applications*, 40(12):4832–4840, 2013.

[64] Angkoon Phinyomark and Erik Scheme. A feature extraction issue for myoelectric control based on wearable emg sensors. In *2018 IEEE Sensors Applications Symposium (SAS)*, pages 1–6, 2018.

[65] Omkar S Powar, Krishnan Chemmangat, and Sheron Figarado. A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals. *Biomedical Signal Processing and Control*, 42:277–286, 2018.

[66] Jinxian Qi, Guozhang Jiang, Gongfa Li, Ying Sun, and Bo Tao. Intelligent human-computer interaction based on surface EMG gesture recognition. *IEEE Access*, 7:61378–61387, 2019.

[67] Anita Rácz, Dávid Bajusz, and Károly Héberger. Effect of dataset size and train/test split ratios in QSAR/QSPR multiclass classification. *Molecules*, 26(4):1111, 2021.

[68] Ashkan Radmand, Erik Scheme, and Kevin Englehart. On the suitability of integrating accelerometry data with electromyography signals for resolving the effect of changes in limb position during dynamic limb movement. *JPO: Journal of Prosthetics and Orthotics*, 26(4):185–193, 2014.

[69] Mamun Bin Ibne Reaz, M Sazzad Hussain, and Faisal Mohd-Yasin. Techniques of emg signal analysis: detection, processing, classification and applications. *Biological procedures online*, 8(1):11–35, 2006.

[70] T Scott Saponas, Desney S Tan, Dan Morris, Ravin Balakrishnan, Jim Turner, and James A Landay. Enabling always-available input with muscle-computer interfaces. In *Proceedings of the 22nd annual ACM symposium on User interface software and technology*, pages 167–176, 2009.

[71] Kevin Scaman and Aladin Virmaux. Lipschitz regularity of deep neural networks: analysis and efficient estimation. In *Proc. Ann. Conf. Neur. Inform. Proc. Syst.*, pages 3839–3848, Montreal, Canada, 3–8 Dec 2018.

[72] Erik Scheme, K Biron, and Kevin Englehart. Improving myoelectric pattern recognition positional robustness using advanced training protocols. In *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 4828–4831. IEEE, 2011.

[73] Erik Scheme and Kevin Englehart. Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use. *Journal of Rehabilitation Research & Development*, 48(6), 2011.

[74] Erik Scheme, A Fougner, Øyvind Stavdahl, Adrian DC Chan, and Kevin Englehart. Examining the adverse effects of limb position on pattern recognition based myoelectric control. In *2010 annual international conference of the IEEE engineering in medicine and biology*, pages 6337–6340. IEEE, 2010.

[75] Miguel Simão, Pedro Neto, and Olivier Gibaru. EMG-based online classification of gestures with recurrent neural networks. *Pattern Recognition Letters*, 128:45–51, 2019.

[76] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. In *Proc. Int. Conf. Learn. Represent.*, Banff, Canada, 14–16 Apr 2014.

[77] Aaron Tabor, Scott Bateman, and Erik Scheme. Evaluation of myoelectric control learning using multi-session game-based training. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(9):1680–1689, 2018.

[78] Miyato Takeru, Kataoka Toshiki, Koyama Masanori, and Yoshida Yuichi. Spectral normalization for generative adversarial networks. In *Int. Conf. Learn. Represent.*, Vancouver, Canada, 30 Apr–3 May 2018.

[79] Sirinee Thongpanja, Angkoon Phinyomark, Franck Quaine, Yann Laurillau, Chusak Limsakul, and Pornchai Phukpattaranont. Probability density functions of stationary surface emg signals in noisy environments. *IEEE Transactions on Instrumentation and Measurement*, 65(7):1547–1557, 2016.

[80] Stefano Tortora, Michele Moro, and Emanuele Menegatti. Dual-myo real-time control of a humanoid arm for teleoperation. In *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pages 624–625, 2019.

[81] Asim Waris, Imran Khan Niazi, Mohsin Jamil, Omer Gilani, Kevin Englehart, Winnie Jensen, Muhammad Shafique, and Ernest Nlandu Kamavuako. The effect of time on emg classification of hand motions in able-bodied and transradial amputees. *Journal of Electromyography and Kinesiology*, 40:72–80, 2018.

[82] Feng Wen, Zhongda Sun, Tianyiyi He, Qiongfeng Shi, Minglu Zhu, Zixuan Zhang, Lianhui Li, Ting Zhang, and Chengkuo Lee. Machine learning glove using self-powered conductive superhydrophobic triboelectric textile for gesture recognition in VR/AR applications. *Adv. Sci.*, 7(14):2000261, 2020.

[83] NI Widiastuti. Convolution neural network for text mining and natural language processing. In *IOP Conf.: Mater. Sci. Eng.*, volume 662, Kazimierz Dolny, Poland, 21–29 Nov. 2019.

[84] Dapeng Yang, Wei Yang, Qi Huang, and Hong Liu. Classification of multiple finger motions during dynamic upper limb movements. *IEEE journal of biomedical and health informatics*, 21(1):134–141, 2015.

[85] Mahyar Zardoshti-Kermani, Bruce C Wheeler, Kambiz Badie, and Reza M Hashemi. Emg feature evaluation for movement control of upper extremity prostheses. *IEEE Transactions on Rehabilitation Engineering*, 3(4):324–333, 1995.

[86] Ping Zhou, Blair Lock, and Todd A Kuiken. Real time ecg artifact removal for myoelectric prosthesis control. *Physiological measurement*, 28(4):397, 2007.