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Review on EMG Acquisition and Classification Techniques: Towards Zero Retraining in the Influence of User and Arm Position Independence

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Abstract: The surface electromyogram (EMG) is widely studied and applied in machine control. Recent methods of classifying hand gestures reported classification rates of over 95%. However, the majority of the studies made were performed on a single user, focusing solely on the gesture classification. These studies are restrictive in practical sense: either focusing on just gestures, multi-user compatibility, or rotation independence. The variations in EMG signals due to these conditions present a challenge to the practical application of EMG devices, often requiring repetitious training per application. To the best of our knowledge, there is little comprehensive review of works done in EMG classification in the combined influence of user-independence, rotation and hand exchange. Therefore, in this paper we present a review of works related to the practical issues of EMG with a focus on the EMG placement, and recent acquisition and computing techniques to reduce training. First, we provided an overview of existing electrode placement schemes. Secondly, we compared the techniques and results of single-subject against multi-subject, multi-position settings. As a conclusion, the study of EMG classification in this direction is relatively new. However the results are encouraging and strongly indicate that EMG classification in a broad range of people and tolerance towards arm orientation is possible, and can pave way for more flexible EMG devices.

Keywords: Electromyography, electrode placement, user-independence, rotation-independence, practical application

1. Introduction

The electromyogram (EMG) is a biological electric signal that manifests around the muscle when a contraction is performed. Since the EMG signal directly relates to the body movement, it can be harvested with electrodes and the corresponding signals can be used by a machine to replicate the human motion. However, the EMG signal is small and easily corrupted with noise from both the environment and within the body. Thus, there are a number of issues to using the EMG as a control signal. Unlike mechanical input methods such as joysticks and buttons which provide a direct interface between input and controller, an EMG system consists of detection and amplification, followed by filtering, feature extraction and classification. Each of these stages presents its own unique set of issues and challenges. Over the years, researchers have continued to debate the relevance of EMG as a control signal. Artemiadis [1] and Jiang et al [2] acknowledged that the high performance of EMG control as reported in research does not necessarily translate into practical consumer devices, citing EMG control difficulties went as far as to suggest input fusion with inertial sensors.

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In addition, Farina and Aszmann [3] suggested that EMG devices lack sensory feedback.

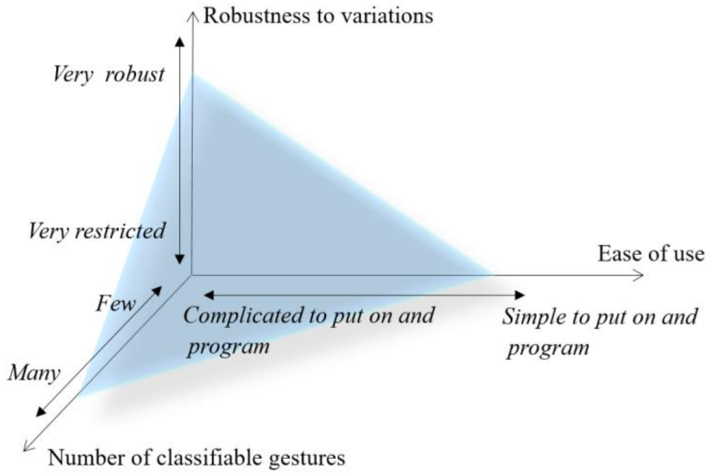


Fig. 1 - The practical limitations of an EMG system is a trade-off between usability, performance and robustness. A simple system should be made to recognise less gestures and a highly robust system should not be expected to be simple in implementation

The attributes of a commercially viable machine input signal lies in its ease of use. Kumari et al. [4] highlighted some requirements of a wearable interface, including comfort, aesthetics and convenience. In [5], eight criteria were identified for general EMG-based ontrol schemes. Among them, the controls should be natural and intuitive, robust to donning on and off, minimal electrodes, short and easy calibration and computationally simple. Classification is the process of comparing the input signal with one stored in the database. In EMG classification, the system is usually first trained with data (usually extracted features) of known gestures. The process of database creation serves to teach the classifier. With sufficient raining data, the classifier can effectively discriminate and predict an unknown feature based on the comparison with values of existing classes.

EMG classification systems can reach very high accuracy rates of over 90% [6–8]. However, the success of these experiments owes it to the clinical setup with precise placement of electrodes and restricted gestures. In reality, there are various issues in practical applications. The EMG classifier requires user-dependent per session retraining [9] and its performance is affected by the slight rotation of the forearm over the course [10]. Furthermore, even for a single user, there is little compatibility for switching between the left and right hand without retraining [11]. The EMG is also susceptible to deterioration if there is strong power line interference (PLI) and electromagnetic (EMI) radiation present in the operating environment [12].

The electrodes must be placed accurately over specific muscles. Thus it is impractical for the general users who are not clinically trained. Moreover, the EMG signal characteristics change because of noise [13] and EMG fluctuations due to physiological changes throughout the day [14, 15]. Next, the EMG classifier will usually require retraining on each session [16, 17]. Due to these limitations, EMG classification accuracy is realistically constrained by the ease of use, robustness to variations and the number of classifiable gestures. The relationship between these three factors is illustrated in Fig. 1. In practice, the actual accuracy is a compromise between these three factors: simple systems will work best with few classifiable gestures, while truly robust systems will have to be complicated. Simultaneously, the more gestures to classify will require limitations to the allowable rotation in the forearm.

This paper aims to explore and evaluate the recent works in electrode placement and classification methods to accommodate variations due to users, arm rotation, and hand-exchange. A vast majority of existing works concentrates on the scope of single-user or single-hand-orientation situations. On the other hand, studies in the direction of improving the universality of EMG acquisition and classification methods are relatively few in comparison. As a result, the main scope of this review covers the electrode placement, feature extraction, and classification methods. The highlight of the review lies in focus on methods used user-independence, rotation-independence and hand-exchange independence EMG classification.

2. Established Trends in EMG Researches

While the EMG is widely applied in healthcare for the diagnosis of neuro-muscular conditions [18] and the design of prosthetic equipment [19], it is also accepted as a viable alternative to machine control interface. Owing to its advantages, EMG has been studied as the control signal for variants of machine interface including human-computer interface (HCI), human-machine interaction (HMI) and human-robot interface (HRI).

2.1 Targeted Placement of Electrodes for Multi EMG Channels

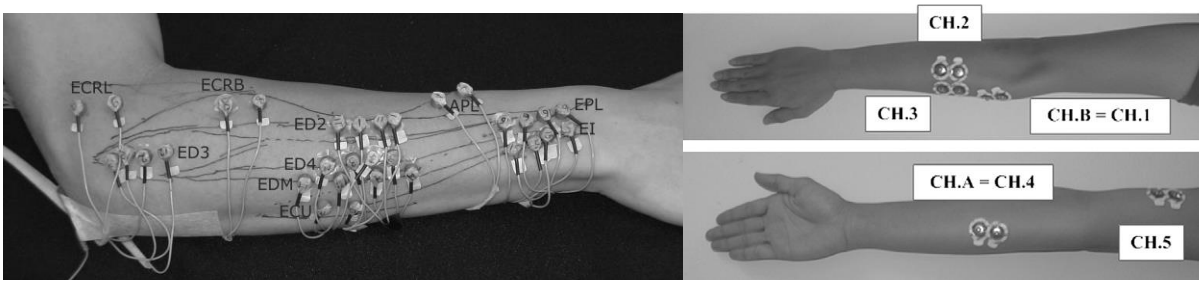
EMG electrode placement are categorized into either targeted to specific muscles or untargeted (symmetric) electrode arrays. The Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles (SENIAM) project provide detailed recommendations for targeted electrode location and orientation with respect to the muscle fibres, skin preparation, amplification and filtering [20]. For the forearm, recommendations on electrode locations for major superficial muscles can be found in Yung and Wells [21]. For accurate electrode placement, SENIAM guidelines include specific location of the muscle, their lead lines and central lead line and body and forearm posture for locating muscles via palpation.

Although a majority of literature reported the placement of electrode pair on the innervation zone (or muscle belly), recent studies have suggested that by doing so, the small geometric changes in the muscle during long-term use can affect the EMG variables [22]. Furthermore, these recommendations pose a challenge because electrodes because electrodes cannot be easily aligned with the muscle fibre direction with certainty [23]. It is clear that targeted electrode placement scheme is time consuming and requires anatomical knowledge.

If the electrode placement could be simplified, then the overall usability will be enhanced as untrained operators can quickly don and doff the electrodes. The untargeted electrode placement scheme involves placing an electrode grid uniformly in equal distance over the forearm. It is easier to don and doff and more suitable for pattern recognition [24], [25]. The targeting of specific muscles can increase classification accuracy [24].

The main objective of using a multi-channel EMG setup is to maximise the number of unique gestures. In multi-channel EMG recording, there are two established methods to place EMG electrodes. The targeted approach places the electrodes precisely over the muscles. With careful placement of electrodes over the specific muscles, highly distinct signals with minimal cross-talk can be obtained. Due to this reason, this method has found more applications in physiological and biomechanics studies, as shown in [6, 7] respectively.

Gesture prediction is also feasible, albeit in a highly controlled setup; [10] performed an elaborate experiment to discriminate the EMG of individual fingers by placing electrode pairs over 10 finger muscles. While the method demonstrates the efficiency of a multi-channel setup in terms of information extraction, it is clearly impractical for machine control, as shown in Fig. 2(a).



(a) *(b)*

Fig. 2 - Electrode placement by (a) Leijnse [10]**; (b) Phinyomark** [26]

More practical multi-channel methods commonly utilise four to eight channels, as adopted by [27] and [16]. With a various combination of features extraction and classification techniques, classification accuracies of above 80% are attainable. Other researchers also explored minimalistic approaches to the issue; [28] experimented with success in classifying five gestures with two electrodes placed over the forearm flexor and extensor muscles. Above all, Mane et al. In [29], it was shown that three gestures could be classified over a single channel over the FDS muscle.

Despite the success of these methods in obtaining superior EMG signals that contribute to excellent classification rates, there are some issues in practical applications. It was evident that the electrodes must be placed accurately over specific muscles. Thus it is clearly impractical for the general users who are not clinically trained. Moreover, the EMG signal characteristics change because of noise [13] and EMG fluctuations due to physiological changes throughout the day [14, 15]. Next, the EMG classifier will usually require retraining on each session [16], [17].

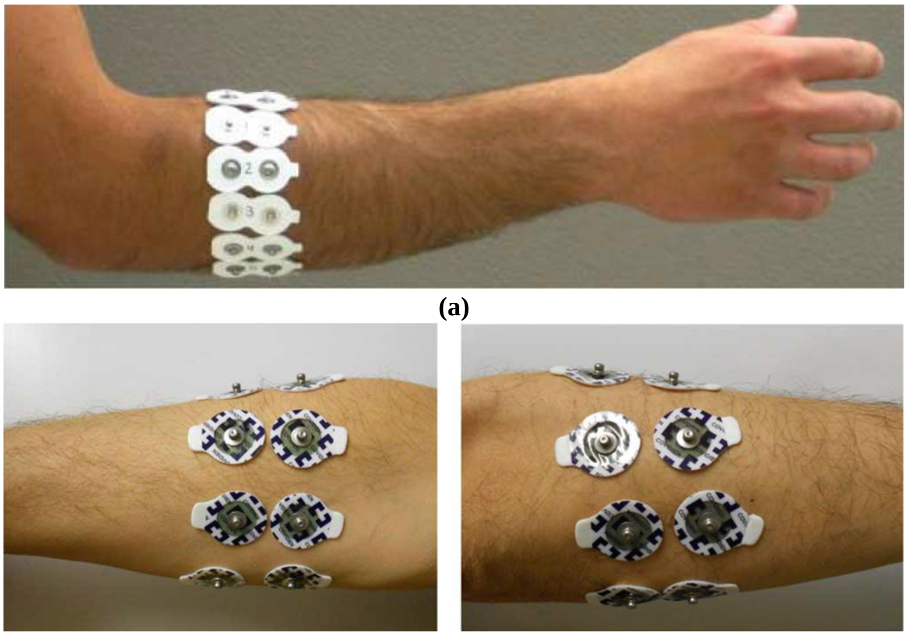
As a result, the success of the methods presented to this point is owed to the careful placement of electrodes, and the controlled environment of the experiment, which is not present in practical scenarios. Practical EMG control application poses a number of challenges, especially in ergonomics and usability [2].

2.2 Untargeted Electrode Placement (Grid Electrode Layout)

A more practical approach towards a better user experience can be achieved by arranging the electrodes into a uniform array covering a circumferential section of the forearm. This approach does not target any particular muscles but instead harvest the EMG signal from a surface area as a 2-dimensional dataset. It is also well established; [30]

introduced a high-density multi-electrode, citing its ability to decompose the EMG pattern into single muscle-unit EMG for analysis. This design shown in Fig. 3 was adopted in [31] for adaptive pattern recognition and [32] for machine control. Compared to the untargeted electrode system, the targeted approach does not always provide the highest classification results [33]. In direct comparison to untargeted systems, the advantage of the targeted system is minimal, in the range of 0-4%, for 1-6 channels [34]. Therefore, the untargeted approach is advantageous in EMG interfaces because it is simpler to implement, while the full advantage of signal isolation of targeted will be preferable for medical purpose.

In **Fig. 4**, the input of the 96 multi-electrode arrays is represented as a colour map. There is ample variance in the colour map to identify the ten gestures under study. Capitalising on the wealth of information from a high density, Xiang et al. [35] classified up to 23 gestures, five sets of 8-channel electrodes placed uniformly along the forearm. Their setup is shown in **Fig. 5.** In a practical sense, the successful classification does not necessitate such high-resolution recording. By using the eight-channel Myo armband on the proximal section of the forearm, Gonzalo and Holgado-Terriza [36] and Zhang et al. [37] reported successful classification of up to 15 gestures. With a correct combination of feature extraction and classification methods, the classifiable gestures can be increased with minimal electrode channels.



(a)

(b) (c)

Fig. 3 - Multi electrode array setup for EMG acquisition; (a) 12 channels [31]**; (b); (c) 8 channels,** [32]**. Each channel consists of a fully differential pair**

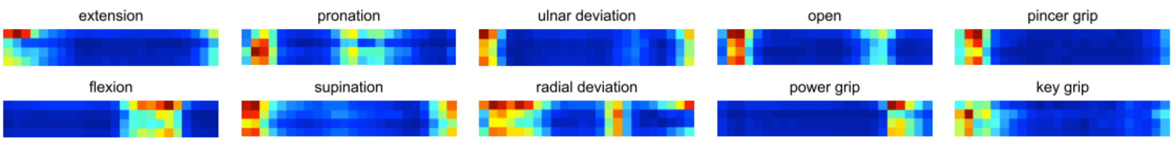


Fig. 4 - Grid representation of forearm gestures. Each pixel represents an electrode channel, [38]

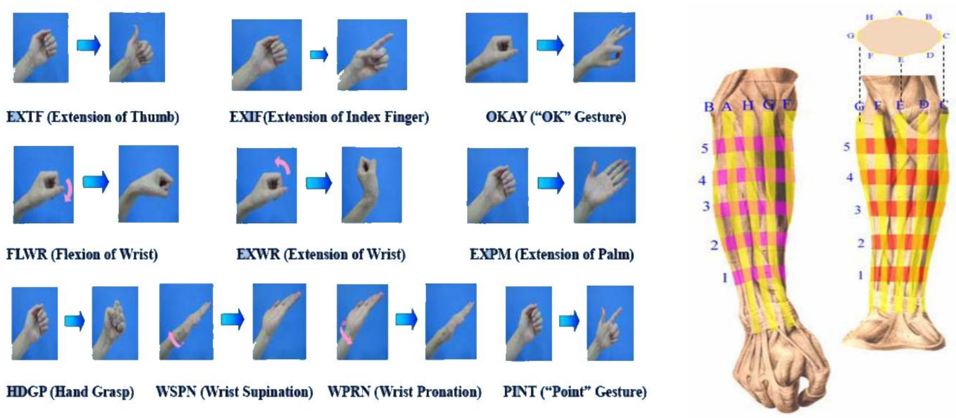


Fig. 5 - Experimental setup for multi-electrode recording of the forearm, [35]

While the multi-electrode setup solves some problems, it also has its own drawbacks. Staudenmann et al. [23] noted that the multi-electrode EMG produces many redundant signals, which requires extended processing. It is also prone to noise contamination of noise and cross-talk [13, 39]. These issues can be alleviated by processing methods which aims to reduce the high dimensional data to a simple linear model [40, 41]. Established tools such as principle component analysis (PCA), k-nearest neighbour (KNN) and correlation analysis methods are well suited to compress and extract useful features from the apparently random EMG signal.

The multi-electrode setup does not escape from the retraining on session, which is an issue that drives a gap between the research and the actual industrial acceptance [42]. Despite that, the multi-electrode setup is nevertheless the right direction towards wearable biosignal devices.

3. The Difficulty of Electrode Placement and its Displacement

While most studies produced very high classification accuracy, the central issue is rarely reported; repeatable electrode placement is not simple. Since muscle locations are physiological and singular, the only reliable method of muscle location is by palpation. It is applied to superficial muscles [43] and finger muscles [44]. Even when a muscle is properly located, longitudinally, the signal can be different amplitude and frequency content which can lead to different interpretation during feature extraction [45]. Therefore, the slightest electrode offset can result in different classification results.

Nevertheless, there are some works that aim to overcome the issues. Young et al. [46] recommended an inter-electrode distance of 4cm towards shift robustness, and 4-6 channels are sufficient for optimal feature extraction. [38] decomposed a 96 channel EMG recording with vision based structural similarity features. Likewise, Stango et al. [47] opted for spatial correlation features with a high density multi-electrode acquisition. While their results did not conclude with complete robustness to both longitudinal and transverse shifts, they showed that classification accuracy does not correlate to arm position. Khushaba et al. [48] and Gu et al. [49] evaluated the compound effect of forearm orientation, muscular contraction and donning-doffing of the EMG sensors. Although the methods could reduce the classification error, they established that per session training is still necessary.

To conclude on the matter, some guidelines on electrode placements do exist [20, 50], however the methods require intimate knowledge of anatomy. To the best of knowledge, there are no simplified guidelines on electrode placement.

4. Training and EMG Variability

Chapter 2 and 3 highlighted the current state of the art of EMG input devices and some of the issues presented therewith. By now, it is now apparent that training is required for both single and multi-electrode setups. While the EMG classification performed well, the procedures were carried out on subject to subject cases. Furthermore, most of the EMG sessions were performed with the position of the arm limited constrained to limit variability in movement.

The EMG signal of a gesture produced by an individual is influenced by the muscle recruitment during the gesture, and inter-subject variations exist in the EMG produced by a group of people. Various factors contribute to its variability. These factors are associated to the physiological condition of the person: gender, age, presence of pain, fatigue or discomfort, or prevention of their onset), their expertise, and the characteristics of the task to be performed [51]. Furthermore, the variability in the pace, range of motion and arm position during repetitive task over long periods can differ by 15% [52]. It is difficult to perform the same task in the exact same manner twice. A simple task of moving an object into a target area by hand required 25 times of training to reduce the variability by 75% [53].

The variations in motion are directly related to the muscle recruitment and the produced EMG also reflect the variability of the gestures across a group of different operators. Therefore, the usability of the EMG system will require robustness towards the variability due to users, hand position and hand side [48].

4.1 Subject-Specific EMG Classification

EMG control applications such as prosthetics and assistive devices are highly personalized towards a specific user. Therefore, if pattern control is implemented, the classifier is trained with only the EMG datafield of the specific user. The consistency of the EMG signals from a single subject contributes towards a high classification rate of 95% and above. With a small sample, Bansod and Raurale [54] has shown that four subjects, when individually classified with linear discriminant analysis (LDA) could achieve subject-specific classification of up to 90%. Taking that into account, even for a larger subject pool of 10 individuals, excellent classification can be achieved; Chu et al. [55] obtained near 100% accuracy for up to nine gestures from features extracted from four channels can be achieved, even with conventional feature reduction tools of principle component analysis (PCA) and SOFM. The SOFM method transforms the PCA-reduced features to a new feature space with improved class separability. Due to the better class separation, the SOFM classifier is able to detect the hyperplane with a better separation margin. Table 1 summarises some subject-specific researches.

4.2 Towards Zero Retraining

Recently, there has been some interest to eliminate retraining. Huang et al. [56] by designing a robust EMG sensor interface to adapt to distortion in EMG recordings due to sensor faults. On the other hand, Liu et al. [17] introduced the common model component analysis (CMCA) framework, where the dissimilarity of LDA trained data from different days were minimized with an optimized projection algorithm. Phinyomark [16] showed that the extracted features can be robust to training data variations. For 11 gestures, the combination of a novel sample entropy feature (SampEn) and LDA classification achieved 93.37% accuracy without retraining. With retraining, the classification accuracy is only 2.5% higher.

4.3 User Independence

Subject independence refers to the feature of the classification method to successfully identify gestures regardless of the subject data. In most cases, the methods centre around identifying gestures which are common for all subjects.

Xiang et al. [35] performed three offline hand gesture recognition to demonstrate cross-user classification: same user, multi user (10 subject data used to train a common classifier for the same group of users) and cross-user (data from 4 users used to recognise gestures of six other subjects). Linear Bayes Normal Classifier was used in their research. The Bayers classifier is a simple probabilistic-based classifier that relies on supervised learning. Their results established that multi-user and cross-user classification results are inferior to that of same-user.

The Myo armband is a popular choice for user-independent studies. In [57], a common classifier was trained with data from all 14 subjects. A combination of up to 10 extracted features were then used to classify 40 different hand gestures. The reported classification accuracy was 97% for 5 gestures but decreased to 16 % for all 40 gestures.

On feature selection, Wahid et al. [58] introduced a novel method called averaged root mean square curve AUC-RMS, which is based on the peak value of the EMG. Tested with the classifiers of k-Nearest Neighbour (kNN), Discriminant Analysis (DA), Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM), it achieved 96.3% accuracy for three simple hand gestures over 10 subjects. RF creates decision trees on randomly selected data samples. Its prediction is obtained from each tree, and the best solution is selected by means of voting. On the other hand, SVM is a supervised binary classifier which predicts a test sample's class by finding a hyperplane in a N-dimensional space that distinctively separates the data points (where N is the number of classes). The signals were normalised to peak values, i.e. root mean square (RMS) and moving average (MAV). In spite of the excellent results, the sample size was relatively small, and only three gestures were studied and has not been tested with more complex gestures. Interestingly, their results show that the simple peak value features can provide good classification results even when compared to more advanced methods.

Increasing the number of subject and gestures poses a challenge to the classifier. Samadani and Kuli´c [59] worked on classifying EMG readings from 10 forearm gestures of 25 subjects with the hidden Markrov model (HMM) method. The HMM is a probabilistic framework which utilises inference algorithms to estimate the probability of each state along every position along the observed data. For the subject-independent recognition, they achieve 49% accuracy for a gesture set with 25 gestures. Additionally, they reported 79%, 85%, and 91% accuracy for select gesture sets with 10, 6, and 4 gestures, respectively. In agreement to [58], the classification error rises with the number of gestures to classify. Therefore, in practice an EMG recognition system should not be used to classify too many gestures.

In the case of Zhang et al. [60], a combination very specific electrode placement, small sample (8 individuals) and a maximum of six gestures yielded a high classification result between 87-93%. In spite of the novel classification method of back-propagation neural network, accuracy was not consistent across the users. The accuracy was found to be different each time for the same individual because the electrode position could not be precisely the same. They suggested that a higher number of channels as in [61] might lead to better classification results. However, that is not necessarily the case. Matsubara and Morimoto [62] used seven channels to classify five gestures from 11 subjects with accuracy of close to 90%.

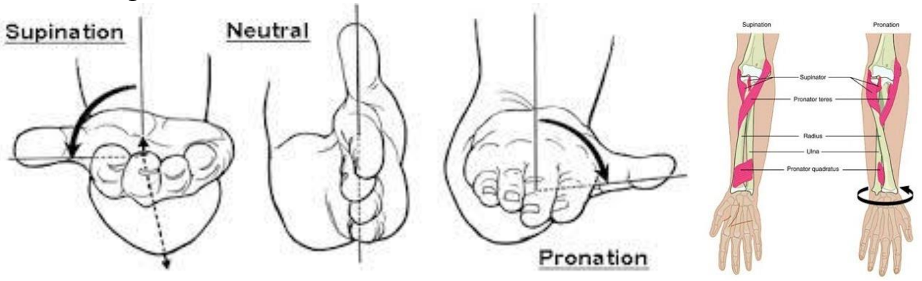
Georgi et al. [63] classified 12 gestures with data from two inputs: Inertial Measurement Unit (IMU) worn at the wrist, and the EMG of muscles in the forearm to infer hand and finger movements. In this experiment, 16 EMG channels were used. The combination of IMU and EMG, provided superior recognition rate of 97.8% in session-independent, and of 74.3% in person-independent recognition. Despite the high number of electrodes, the classification with EMG alone, dropped drastically to just 25 – 45%. Therefore, the processing methods and selected gestures play a more significant role rather than the number of channels.

Other literature also explored user independence with multiple input devices in conjunction with the EMG sensors. With the additional input data from force sensors, Castellini et al. [64] obtained classification accuracy of up to 97% for three gestures from 10 subjects. Seven electrodes were placed on specific finger and thumb muscles and data analysis was done with simple RMS feature and SVM classifier. With the combination of classic and novel processing methods, the additional data from accelerometers [65] and motion capture [66] contributed to very high classification accuracies of over 90%, even for a subject base of 40 individuals.

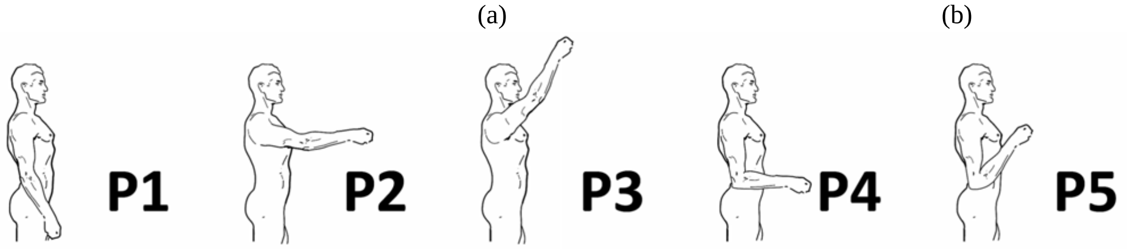
As a conclusion, establishing a subject independent EMG input system is not a straight forward process. The main reason is due to electrode positioning [37] and the unavoidable individualistic nature of the EMG, where even biometrics is possible [67]. A comparison of user-independent works is shown in Table 2.

4.4 Rotation and Position Independence

The forearm is a highly articulated limb, which is actuated by many muscles. For a given gesture, i.e. flexion and rotation, the corresponding EMG can vary even for a single individual. Fig. 6 (a) and (b) shows the forearm in pronation and supination and how the muscles shift during rotation, while Fig. 6 (c) shows the forearm in multiple positions. The gestures when performed in conjunction with wrist rotation will result variations in EMG signals due to the activity of the pronator and supinator muscles [21]. Therefore the EMG system should also be robust towards the forearm EMG varies according to the forearm rotation.



(a) (b)



(c)

Fig. 6 - How the forearm rotates. The forearm in (a) supination and pronation; (b) Besides the shift in muscles, EMG signals from the pronator and supinator will also be detected on the surface; (c) Arm position classification [68]**,** [69]

In [70], it has been reported that the EMG changes as much as 25% due to forearm rotation. Considering the rotation in distance, the classification results of five gestures dropped from an average of 77% at distance zero to 63% at the extremities. Showing similar trends the misclassification of forearm signals correlates to wrist rotation rather than hand position [9], [71]. Bitzer et al. [72] obtained classification results of six finger gestures with excellent rotation independence in their literature. However, the electrode placement was clinical - placed specifically over 10 finger muscles around the forearm. Finger muscles are deep muscles, which are more difficult to locate.

To improve classification accuracy, some works have proposed EMG in conjunction with accelerometers.

Classification accuracy could be improved by Their method effectively reduced classification error from 18% to 5% [65, 66] & [68]. The method was applied to 10 able-bodied subjects, using 8 channels of wet electrodes. Eight gestures were classified with LDA and time-domain (TD) features. Therefore, an improved classification accuracy can be achieved with multiple methods as opposed to solely EMG [69]. Recent works related to rotation and position independence are available in Table 3.

4.5 Hand Exchange Independence

Hand-exchange is defined as a switch between the left to right hand or vice-versa. Comparatively, there are far fewer researches in this area. In an early investigation, Kim et al. [73] noted negligible difference in the EMG of the left and right hand. In a later in-depth study, Khushaba [11] has proven otherwise - the data field of the opposite hands are relatively different. However, there is little surprise as Kim's work minimalistic in nature, focusing on just three gestures over a single channel while Kushaba studied multiple gestures over 10 channels. When the training and test hand exchange was performed. The average classification result was about 10% lower. Table 5 shows the available work on classification in hand-exchange independence.

5. Discussion and Conclusion

Traditional EMG systems requires training upon application, which greatly compromise user experience. Furthermore, the variations in user and forearm orientation further complicates the quest for universal compatibility and robustness. Although the vast majority of EMG researches were conducted on single-user, single-position situation, emerging works to accommodate these variations have shown positive results.

5.1 Electrode Placement

To move towards general practicality and user-independence, first a grid electrode layout in wearable form should be recommended. On the processing front, the multi-electrode setup offers several advantages. The higher density grid provides a superior spatial resolution of muscular activity and contains multidimensional information suitable as an input for pattern recognition. In addition, the arrangement of a grid electrode in the form of a sleeve is simpler to don and doff. The human muscles have a rich diversity in muscle fibre directions. The guidelines recommended by the *surface EMG for non-invasive assessment of muscles* (SENIAM) project provides general guidelines for electrode locations and placement procedures. However, the misalignment of electrodes towards the muscle fibres can reduce the EMG amplitudes. These recommendations, including [39], [40] pose a problem because the electrodes cannot be easily aligned with the muscle fibres with certainty and cannot always be possible. Therefore, a higher-density electrode grid setup can collect more EMG signals over a surface area. However, a high-density EMG recording contains redundant data. Dimensional reduction techniques such as principle component analysis (PCA) can be used to detect these multivariate redundancies and reduce the data for faster and more accurate classification [23]**,** [74]**.**

5.2 Classification in the Influence of User and Arm Orientation

EMG signals have potentials in a broad range of applications, including controlling prosthetic devices, human-assisting manipulators and sign language recognition. Acquisition apparatus such as sensors and amplifiers are now inexpensive and easy to use. However, most available EMG classification algorithms are subject-specific due to the complexity of the signals influenced by anatomical and physiological differences between individuals. This includes muscle construction, contraction level, electrode location and even sweat from the skin. These differences contribute to the variability of the EMG feature values, where the EMG signal can be different even for the same gesture. As a result, the capacity for effective classifier training and prediction is consequently degraded [58]. Present studies, however, show that multi-subject gesture detection accuracy can be improved significantly without the need for single-subject training. Although subject-independent gesture classification accuracies can be comparable to single-subject, classification systems trained for multi-user may not perform as well for subject-specific gestures [62], [63].

On forearm rotation, the EMG TD features and training in a single position generally yields a higher classification error compared to classification in multiple positions. There are several reasons for this dependency: first, the muscle recruitment changes with the limb position to stabilise the limb due to gravitational forces. Next, electrode shift occurs due to the change in muscle shape, length and position during limb movement. As a result, better classification results can be obtained if training is done in multi-position rather compared single-position [68], [69].

5.3 Suggestions for Future Work

The presented literature suggests several directions for future studies in improving the practicality of the EMG control system regarding robustness towards EMG dynamics due to user and forearm variations. To the best of knowledge, the combined influence of EMG dynamics due to user-independence, rotation independence and hand-exchange independence has not been investigated. Future research can be directed towards overcoming the influence of these EMG dynamics:

- As seen in the literature presented here, all classifiers are capable of highly accurate prediction. Compared to classifiers, the features play a more critical role for achieving a robust performance against the combined EMG dynamics due to user and arm orientation [49]. Khushaba et al. [48] have also pointed out that the performance of the classifier can be improved by using feature extraction methods that rely on the angular information of muscle activation patterns, and recommended features such as discrete Fourier transform based features (DFT) TD power spectral descriptors (TD-PSD).
- . Classifiers, on the other hand, could be selected with processing time as a priority. For example, traditional classifiers such as LDA and KNN are much faster than SVM. Advanced machine learning methods such as wavelet neural networks, hybrid classifier and Negative Correlation Learning (NCL) can be considered in future work.
- As it has been shown in [58] & [59], the classification accuracy generally decrease with the number of gestures to classify. Xiang et al. [35] has also reported that for same number of gestures, different group of gesture combinations produced varying overall accuracy. Therefore, the selection of gestures can affect the overall classification accuracy and the classifier performance can be improved by the careful selection of gestures.
- The sampling rate of the data acquisition can affect the classification accuracy. As recommended by Phinyomark et al. [75], an EMG sampling rate at 1000 Hz and above can provide up to 9% higher classification accuracy compared to a sampling rate of 200 Hz. Future research may consider this point as some consumer-grade EMG devices including the MYO has a sampling rate of 200 Hz.

Table 1 - Comparison of single-subject gesture classification

Feature	Classifier	Highlights	Sample size	Accuracy	Reference
MAV, VAR, SD, ZC, SSC, WL,	LDA	Subject specific, 6 wrist gestures*	4	90%	Bansod et al. (2015) [54]
Wavelet transform , PCA, Self Organizing Feature Map	Multilayer projection	Subject specific, 9 wrist gestures*	10	95 - 99%	Chu et al. (2006) [55]
Linear envelope, various frequencies	Distance-based Decision Classifier (DDC)	Classification of up to 50 wrist and finger gestures, 6-12 successful*	3 (amputees)	47 - 62%	Atzroi & Mu (2015) [76]
RMS	SVM	Subject specific hand grip, 3 gestures, with aid of force sensors*	7	95% - 97%	Castellini et al. (2009) [64]
N/A	Cross-correlation	Muscle change in geometry during forearm rotation*	7	48%-82% (proportion of muscles in forearm rotation)	Yung & Wells (2013) [21]
MAV, VAR, maximum value	LDA	Arm location, subject specific wrist gestures with the aid of accelerometers	5 (amputees)	92% (interposition) 60% (intraposition)	Geng & Li (2012) [71]

Table 2 - Comparison of user-independent gesture classification

Feature	Classifier	Highlights	Sample size	Accuracy	Reference
AR, MAV, WL, ZC, SSC,	Common model component analysis, based on LDA	Independence of wrist and finger gestures to electrode shift*	5 (amputees)	75 - 95%	Liu et al. (2015) [17]
MAV, AR	Linear Bayes Normal Classifier	User independence, up to 23 wrist gestures*	20	76.7%-90.2%	Xiang et al. (2009) [35]
MAV, RMS, Energy ratio, histogram, VAR, ZC, MNF, MDF	SVM	Subject independence, up to 40 gestures, in groups of 5, 6 and 8 tasks+	14	15% - 90 %	Kerber et al (2017) [57]
MAV, ZC, WL, SSC normalised with Averaged root mean square curve	KNN, DA, NB, SVM, RF	Subject independence, 3 gestures*	10	96.3%	Wahid et al. (2018) [58]
Linear envelope	HMM	Subject independence, 4-10 gestures*	25	70%-81%	Samadani & Kulic (2014) [59]
SD, MAV	Back-propagation neural network	Subject indendent wrist gestures, 6 gestures*	8	87%-93%	Zhang et al. (2019) [60]
Bilinear modelling	Multi-class SVM	Subject independent wrist gestures*	11	90%-60%	Matsubara et al. (2013) [62]
SD	HMM	12 subject independent wrist gestures, with aid of accelerometers, 12 gestures+	5	35%-55% (EMG) 70-80% combination of sensors	Georgi et al. (2015) [63]

Table 3 - Comparison of rotation independence gesture classification

Feature	Classifier	Highlights	Sample size	Accuracy	Reference
Linear envelope	SVM	Position independence, subject specific wrist and finger gestures with the aid of motion tracking sensors+	8	49%-70% (EMG) 45-65% (with motion sensor)	Yang et al. (2017) [9]
MAV, Autoregressive Correlation	HMM variations	Position independence, many subject specific. 5 wrist gestures with the aid of accelerometers*	2	56% - 99% (EMG only) Up to 100% (combination of sensors)	Xu et al (2011), Stival et al (2019) [65, 77]

Table 4 (continued) - Comparison of rotation independence gesture classification

Feature	Classifier	Highlights	Sample size	Accuracy	Reference
N/A	SVM	Position independence, 6 subject specific wrist gestures*	1	Up to 95%	Bitzer et al. (2006) [72]
RMS	SVM	Position independence, subject specific finger gestures. 3 gestures classified+	12	63%-77%	Saponas et al. (2009) [70]
Various TD features, accelerometer	LDA	Position independence, subject specific hand gestures, 8 gestures in 5 positions+	17	3.8%- 21.1% error	Fouger et al. (2011) [68]

Table 5 – Comparison of hand-exchange independence gesture classification

Feature	Classifier	Highlights	Sample size	Accuracy	Reference
CCA projection	LDA, KNN, SVM	Hand exchange independence, 4 wrist gestures+	8	72-80%	Khushaba (2014) [11]
21 various time, frequency domain features	SVM, LDA, PNN, KNN, AdaLDA	Hand exchange independence, position independence, 14 wrist gestures+	6	Significant drop in accuracy for hand exchange	Gu et al. (2018) [49]
Maxmimum, minimunm, mean, VAR, signal length, RMS, fundamental frequency, Fourier Variance	KNN, Bayes	Hand exchange independence, 4 wrist gestures+	1	Almost 100%	Kim et al. (2008) [73]

* Targeted electrode placement, + Untargeted electrode placement

AdaLDA- adaBoost-LDA, AR- auto-regression, CCA- canonical correlation analysis, DA- discriminant analysis, DDC- distance based decision classifier, HMM- hidden Markov model, KNN- K-nearest neighbour, LDA- linear discriminant analysis, MAV- moving average, MDF- median frequency, MNF- mean frequency, NB- naïve Bayers, PCA- principle component analysis, RF- random forest, RMS- root mean square, SD- standard deviation, SSC- slope sign change, SVM- support vector machine, PNN- probabilistic neural network, VAR- variance, WL- wavelength, ZC- zero crossing

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