© Universiti Tun Hussein Onn Malaysia Publisher's Office

IJIE

The International Journal of Integrated Engineering

Journal homepage: http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The Classification of EMG Signals with Zero Retraining in the Influence of User and Rotation Independence

Zinvi Fu[1*], A. Y. Bani Hashim[2], Z. Jamaludin[3], I. S. Mohamad[4]

[1]Politeknik Kota Kinabalu,
No. 4 Jalan Politeknik, KKIP, Kota Kinabalu, 88460, MALAYSIA

[2-4]Universiti Tenikal Malaysia Melaka,
Jalan Hang Tuah Jaya, Durian Tunggal, 76100, MALAYSIA

*Corresponding Author

DOI: https://doi.org/10.30880/ijie.2021.13.01.011
Received 4 March 2020; Accepted 20 July 2020; Available online 30 January 2021

Abstract: The surface electromyogram (EMG) contains information directly related to muscle contraction and modern classification techniques can obtain near-zero error when identifying various gestures over the forearm. However, good results come at a compromise over the ease of use. Once the EMG classifier trained on a user is changed, the accuracy rate will be greatly reduced. Furthermore, changing the position of the forearm also causes drop in accuracy rate. Acknowledging the limitations of EMG classification, this study aims to investigate the EMG signals based on the gestures, and evaluate if there are any gestures which are inherently robust to these variations. The EMG of forearm gestures have been classified in the combined influence user independence, rotation independence and hand exchange independence. Experiment results on 20 participants indicated that truly independent classification can be achieved for most forearm gestures (up to 100%) in some arm positions. Hand exchange is also not feasible as the study has shown that the data field for both hands are fairly different. Out of the nine gestures under study, only the wrist extension was found to be truly independent of all the influences.

Keywords: Electromyography, hand gesture classification, user-independence, rotation-independence, hand-exchange independence

1. Introduction

The ectromyogram (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. 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 researches does not necessarily translates into practical consumer devices, citing the difficulties of EMG control and went as far as to suggest input fusion with inertial sensors. Concurring to that, Farina and Aszmann [3] suggested that EMG devices lack sensory feedback.

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; which in the list includes comfort, aesthetics and convenience. EMG classification systems can reach very high accuracy rates of over 90% [5–7]. However, the success of these experiments owe it to the clinical setup with precise placement of electrodes and restricted gestures. In reality, there are some issues in practical applications. The EMG classifier would require user dependent per session retraining [8]. Performance will also suffer if the forearm rotates slightly during the course [9]. Furthermore, even for a single user there is little compatibility for

*Corresponding author: zinvifu@polikk.edu.my

switching between the left and right hand without retraining [10]. The EMG is also susceptible to deterioration if there is strong power line interference (PLI) and electromagnetic (EMI) radiation present in the operating environment [11].

It is obvious 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 [12] and EMG fluctuations due to physiological changes throughout the day [13], [14]. Next, the EMG classifier will usually require retraining on each session [15], [16]. Considering the limitations of the EMG classification, the classification accuracy is realistically limited by the ease of use, robustness to variations and the number of classifiable gestures. The relationship of these three factors are illustrated in Fig. 1. It is obvious that the actual accuracy is a compromise between these three factors: simple systems will work best with few classifiable gestures, while truly robust systems will be have to be complicated. At the same time, the more gestures to classify will require limitations to the allowable rotation in the forearm.

Acknowledging the shortcomings of a practical systems, some researchers have work towards providing robustness towards those variations. In [17], they introduced a novel method called averaged root mean square curve AUC-RMS, which is based on the peak value of the EMG. It achieved 96.3 % accuracy for three simple hand gestures over 10 subjects. 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. On the other hand, in [18] the forearm gestures of 25 subjects was classified with as accuracy as low as 49 % for 25 gestures.

The forearm is a highly articulated limb, which is actuated by many muscles, and these muscles shift during rotation [19], where classification accuracy can drop from 77 % to 63 % . Processing techniques introduces by [20] improved classification rate. On hand exchange, [10] have demonstrated that the two hands produce fairly different data field, even for the same user. Therefore the two hands should be trained separately. While these methods studied the effect of EMG variations, they did not account for the combined effect of the issues.

Therefore this study narrows the research gap by presenting combined issues of user, rotation, hand swap and noise onto the EMG classification accuracy, and make recommendations based on the classifiable gestures. By acknowledging the limitations of EMG in practical application, the objective of this study is to identify gestures which are robust towards these variations.

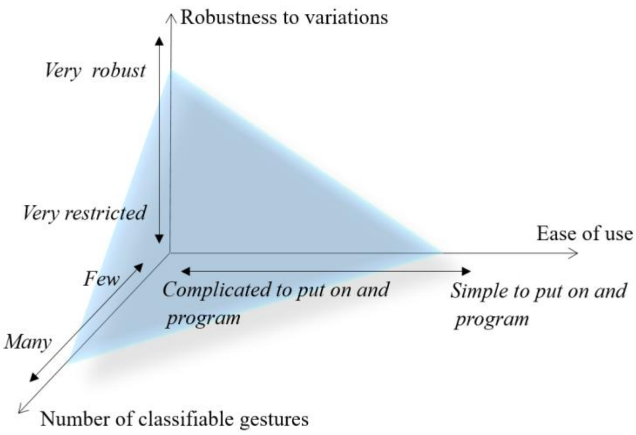


Fig. 1 - The practical limitations of an EMG system is a trade-off between usability, performance and robustness. A simple system should be made to recognize less gestures and a highly robust system should not be expected to be simple in implementation

2. Methodology

The experiment is divided into two stages. The objective of the first stage is to acquire the EMG signals for user independece, rotation and hand independence. The process was repeated on the right hand. In the second stage, the EMG signals were decomposed into the peak EMG feature followed by classification with linear discriminant analysis.

Prior attaching electrodes, the subject skin was cleaned with alcohol but not shaved. Then, six pairs of electrodes were placed evenly around the lower forearm of the left hand. The Six electrode pairs were placed with equal distance, d_e around the lower forearm, at about 30 mm below the elbow. A brief schematic of the electrode placement relative to the body can be found xxx. With the arm at neutral position, placing began with CH2 placed directly below the elbow, on the posterior side of the forearm. The other channels are then placed at $d_e = \frac{1}{6} \times$ circumference. With the electrodes placed, the electrodes were connected to the EMG amplifier with shielded cables.

The subjects were asked to perform nine gestures, which in sequence are flex (FLX), extend (EXT), abduct (ABD), adduct (ADD), open (OPN), close (CLS), finger (FIN), OK (OKE) and thumb (TMB). The nine gestures are shown in

Fig. 3. Subjects performed the gestures with the left hand in neutral position, followed by supination and pronation. The subjects performed nine gestures in successions and the EMG was recorded into six individual channels. The electrode locations are shown in Fig 4 (a) and (b).

To investigate if the lower forearm muscles are immune to muscle shift due to pronation and supination, the gestures were also performed with the hand in pronation and supination. All gestures and their positions are listed in Table 1.

The gestures were performed in a succession sequence. Subjects were asked to perform the gestures beginning with the wrist flexion and ending with the thumb gesture. The gestures were performed at a contraction which the subject is comfortable with, having no load was applied. In Fig 4 (c), (d) and (e), the three positions of neutral, pronation and supination are shown. Due to the weight of the cable, a sleeve was worn over the electrodes to keep in place.

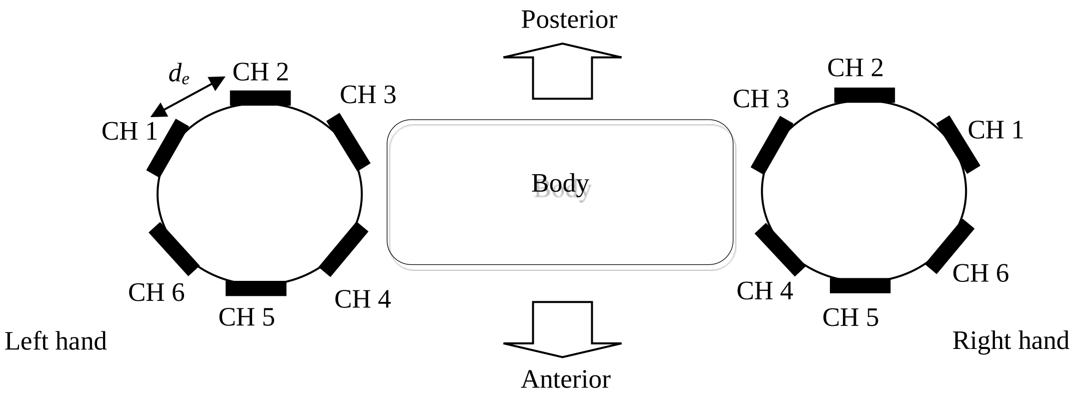


Fig. 2 - General view of the electrode placement viewed from the top. The six channels are placed on a uniform distance around the circumference of the forearm directly below the elbow

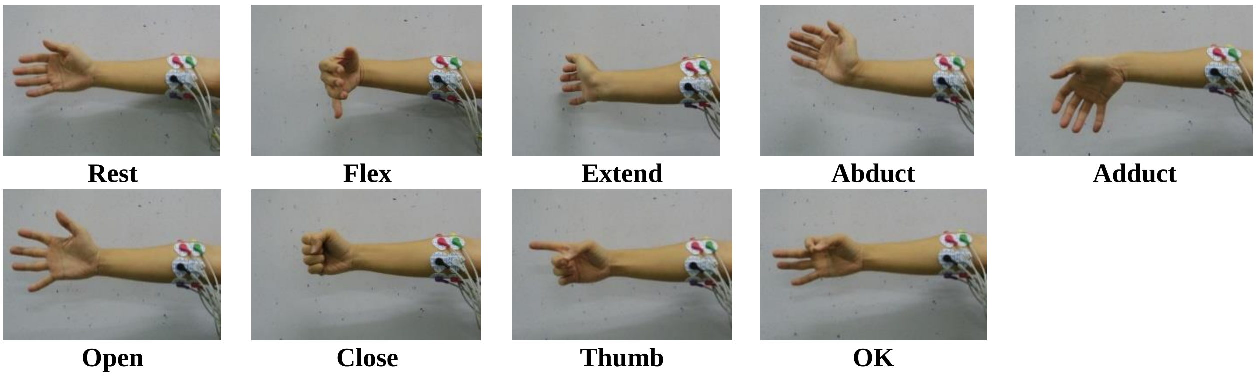
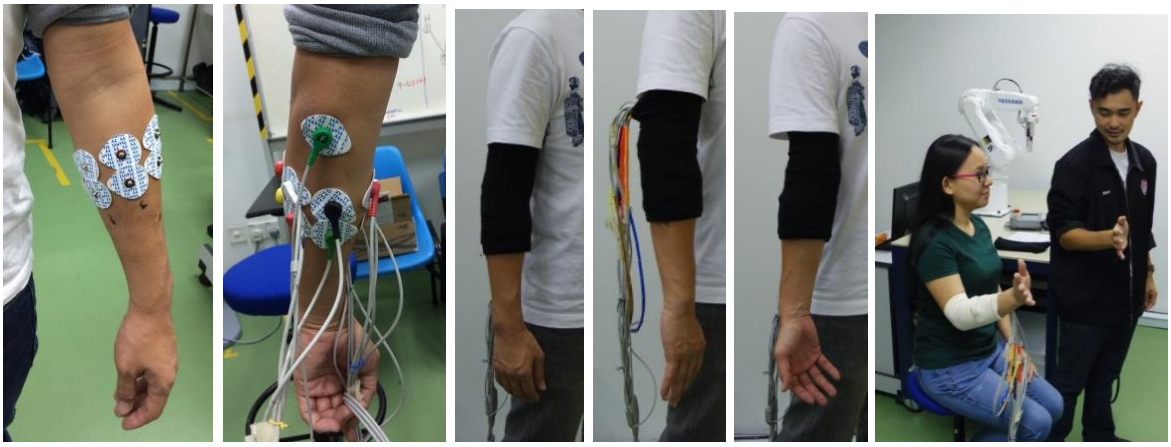


Fig. 3 - Gestures performed for classification. There are six wrist gestures: FLX, EXT, ABD, ADD, OPN and CLS; and three finger gestures: FIN, TMB, and OKE. The gestures were recorded in sequence with the arm down in natural position

To avoid error due to wrongly performed gestures, the gesture sequence was recorded at least three times per position. In each sequence, individual gestures would last about 1.5 to 2 s, followed by a period of rest of equal time span. Each sequence of nine gestures lasted between 30-40 s.Due to the duration of the procedure, the subjects were given the choice to either stand or sit. The photograph shown in Fig 4 (f) shows a subject practicing the gesture sequence prior to actual recording.

2.1 Subject Demographics

In this study, 20 subjects which consisted of 10 male and 10 female subjects were selected. Prior to the procedures, the subjects have signed the consent form. The subject demography ranges from age 24-42 with mean age of 30. The subjects BMI range from 15 to 32 with a mean of 23, with 55% having a normal BMI class. No subjects reported any accident and pain associated with the wrist and finger. However, two subjects one male and female, reported having mild essential tremor. All subjects in this study are right handed.



(a) (b) (c) (d) (e) (f)

Fig 4 - The positions of the electrodes (a) front view (b) rear view, arm position (c) neutral (d) supination (e) pronation (f) general view of procedure during recording.

Table 1 - The gestures and the positions they are performed in nine gestures were performed in three positions on both hands

Gesture		Position		Hand	
Flex	FLX	Neutral	DN	Left	LH
Extend	EXT	Pronated	DP	Right	RH
Abduct	ABD	Supinated	DS		
Adduct	ADD				
Open	OPN				
Close	CLS				
Thumb	TMB				
Finger	FIN				
OKE	OKE				

2.2 Equipment Used

An EMG amplifier was developed specifically for this experiment. The EMG amplifier is based on INA121P instrumentation amplifier and has an effective CMRR of 78.64 dB and adjustable gain of 250. Basic filtering incorporated into the design consists of a band pass filter with the range of 18.97 Hz to 709 Hz. Further details on our design can be found in [21] and [22]. Ag-Cl wet electrodes were used in this experiment. Each channel consists of two electrodes. To further reduce noise, a reference electrode is necessary and was attached to an electrically inactive part of the body; in this case the bone of the elbow. Further isolation from the common-mode noise was done with a shielded cable which connected the EMG amplifier to the electrodes.

The data was acquired with the National Instruments NI-cDAQ 9178 data acquisition unit with the NI9205 module, sampled at 5 kHz and Labview as the user interface. Subsequent conditioning, feature reduction and classification was performed with the Matlab 2010 software.

3. Results

Shown in Fig. 5 (a), are the raw EMG output of the gestures performed by subject F01. The channels exhibit low baseline noise with the exception for CH5 and to a lesser degree in CH6, which was due to ECG contamination. The similarity in CH1 and CH2 indicate co-activation in the region covered by the two channels, possibly due to overlapping muscles. On the gesture detection, CH1 shows better separation for the ABD and CLS gestures. In comparison, CH3 and CH4 shows a different pattern with more significance in the FLX, ADD, CLS FIN and TMB. Despite the ECG interference in CH5, the recorded pattern evidently reflect those of CH4 with the exception of a slightly higher amplitude in the OPN gesture. The EXT and OPN gestures were most significant in CH6. Therefore, the six channels setup can provide enough information to detect unique EMG patterns for each gesture.

The stochastic, time-varying nature of the raw EMG signal is computationally complex to analyze. Therefore simplification is necessary. For this purpose, the linear envelop was produced by rectifying the signal by applying a modulus to the EMG signal defined as x(t) where:

$$x(t)_{rect} = |\,x(t)| \qquad (1)$$

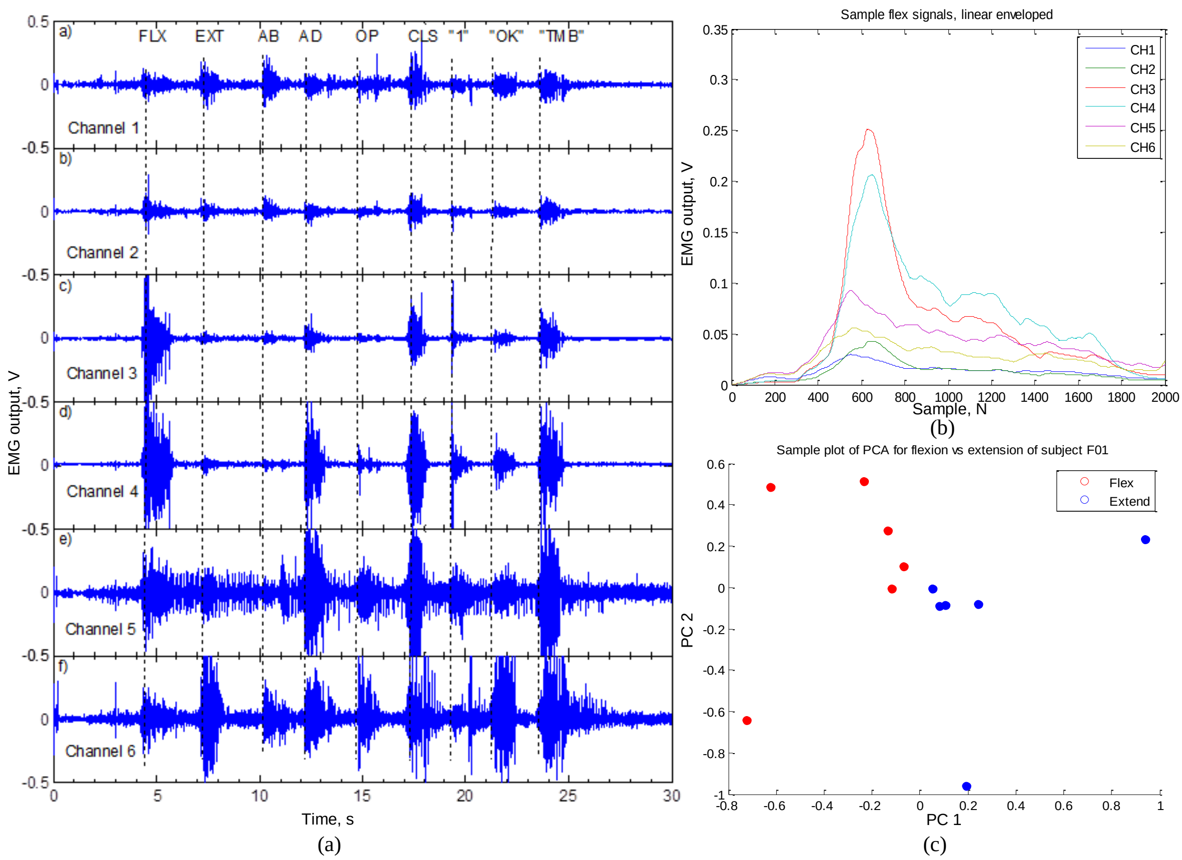


Fig. 5 - Sample results of subject F01 EMG acquisition for the FLX gesture, showing (a) the raw EMG output for CH1 to CH6, (b) linear envelope output and (c) PCA reduced features for flex and extend of the six channels. The flex and extend gestures produce distinct for a single subject. However, variations will increase with the size of the subject pool

The rectified waveform was then applied with a second-order Butterworth filter with a cutoff frequency of 10 Hz to extract the linear envelope feature. These gestures produce very distinct patterns. However, variations will be introduced as the subject pool increases. In Fig. 5 (b), the processed FLX gesture shows a simplified EMG pattern of the muscle contraction: typically observed as a rapid rise in EMG amplitude, followed by a gradual fall as the muscle contract. Consistent to the raw EMG data, CH3 and CH4 peaked at a significantly higher amplitude compared to other channels.

The linear envelop feature is then processed with principle component analysis (PCA) to reduce the dimensionality of the time varying EMG waveform. PCA is an orthogonal linear transformation that de-correlates multivariate data and projects it onto a new coordinate system such that the greatest variance in the data lies on the first coordinate while the least variance in the data tends to lie on the last coordinate [23]. This results a decomposition into a series of principle components (PC). In this example, the first PC accounts for 85% of the variance while the second PC accounts for 7%. Fig. 5 (c) shows the PCA plot of the first two PCs where PC1 is projected on the *x-axis* and PC2 is projected on the *y-axis*. The combination of these two PCs will account for 92% of the variance.

The objective of using PCA is to compress the data by removing repetitive data while extracting only the significant variation. A reduced dataset will allow quicker and more accurate classification. The LDA is a supervised classifier, whereby classes must be pre-defined before training is done. LDA works on the principles of Bayes' Theorem which estimates the probability of the data belonging to each class. With the input class as *x(k)*, probability of the output class (k) is given by,

$$P(Y = x|X = x) = \frac{\left(PI_k.fk(x)\right)}{\sum\left(PI_l.fI(x)\right)} \qquad (2)$$

PI_k refers to the base probability of each class (k) observed in the training data, defined as:

$$PI_k = \frac{nk}{n} \quad (3)$$

The LDA assumes the probability of x belonging to a class is, f(x) is Gaussian. Therefore, the discriminant function *Dk(x)* is given as:

$$Dk(x) = x\left(\frac{\mu k}{\sigma^2}\right) - \left(\frac{\mu k}{2\sigma^2}\right) + \ln(PI_k) \quad (4)$$

Dk(x) is the discriminate function for class *k*, given input *x*.

Fig. 6 shows the average 20 subject time domain features of each gesture across each channel, in pronation and supination and a comparison between both hands. Although a mean pattern can be established for each gesture, the variations, shown as standard deviation in the inset is high. Generally, the wrist gestures would produce higher variations compared to the finger gestures (FIN, OKE, TMB). The variations are due mainly to physiological issues, and how much force the subject exerts when performing the gestures.

Table 2 shows the classification results of the user independence test. The overall classification results for the user independence classification test. The data here is trained and tested against itself. The classifier was trained with only one gesture data per subject. There was no per subject retraining. In the DN position, LH classification results are good, obtaining up to 100 % accuracy for the gestures, with the exception of OPN and CLS. Classification accuracy drop when classified in pronation and supination. However for the RH, classification results were observed to be lower. Despite the non-retraining and wide variation of data from various users, the DN position provided good classification results. This is a strong indication that user independence is possible in the DN position.

Table 3 shows the results of the rotation independence test. In this test, training data was taken from the DN position and the test data was taken from the DP and DS position. Classification accuracy dropped for most gestures, especially in the DS position. Again, the performance of the left hand does not reflect in the right hand. The classification result of the right hand has no correlation to the left hand. The accuracy is maintained in the LH EXT, ABD and FIN gestures while the RH does not show the same obvious pattern.

Table 2 - Cross user classification accuracy: The LH classification results do not reflect to the right hand. Only the DN gestures are consistent

	LH, %			RH, %		
	DN	DP	DS	DN	DP	DS
FLX	75	80	75	90	75	65
EXT	90	95	70	90	80	100
ABD	90	100	80	55	55	95
ADD	75	85	70	60	60	65
OPN	60	75	55	50	45	45
CLS	35	45	65	65	65	55
FIN	80	65	70	90	85	70
OKE	95	85	65	45	50	45
TMB	75	75	75	90	60	80
Mean accuracy	75	78	69	71	64	69

The switch from DN to DP in the LH result a significant classification rate drop, most significantly in FIN and CLS with a difference of -30 % and -5 % respectively. On average, the mean accuracy dropped from 75 % to 70 %. For DN-DS gesture, the classification rate was further reduced to 47 %. With the exception of EXT, ABD and ADD, all gesture was classified at 50 % and below with the CLS at only 5 %. For the RH, shifting from DN to DP and DS caused the mean classification to drop from 71 % to 70 % and 69 % respectively. Only the EXT gesture maintained consistency across the rotation. Unlike the LH, All gestures experience considerable drop in classification accuracy.

Based on the results, it can be concluded that the rotation affects the EMG signals. The signals in neutral, pronation and supination are distinct and must be classified as separate classes.

Table 3 - Classification attempt of DS and DP with DN as training data. The classifier was trained with DN gestures and tested with DP and DS. It can be observed that rotation affects most of the signals with the most acceptable result being the EXT gesture. Again, the accuracy of the right hand is lower than the left hand

	LH, %			RH, %		
	DN-DN	DN-DP	DN-DS	DN-DN	DN-DP	DN-DS
FLX	75	70	50	90	90	65
EXT	90	80	60	90	90	100
ABD	90	90	45	55	55	95
ADD	75	75	65	60	60	65
OPN	60	65	45	50	50	45
CLS	35	30	5	65	65	55
FIN	80	50	25	90	65	70
OKE	95	90	60	45	90	45
TMB	75	75	65	90	45	80
Mean accuracy	75	70	47	71	70	69

Table 4 shows the results of the hand swap independence. The training data is taken from one hand and tested on the other. With the classifier trained with LH data, it was tested with data from the RH, and vice versa. The goal of this procedure is to determine if the EMG interface trained with one hand is compatible with the other. The results show that average classification was below 50% for the LH trained, tested with RH signals. On the other hand, RH trained tested with LH signals was marginally better with just above 50%. Among all the gestures, the EXT was the most compatible across the hands with an average of 78% on the LH and 85% on the RH, followed by FLX with an average of 58% and 72% for LH and RH respectively. The average was calculated by taking the mean of the signal in all three rotation position.

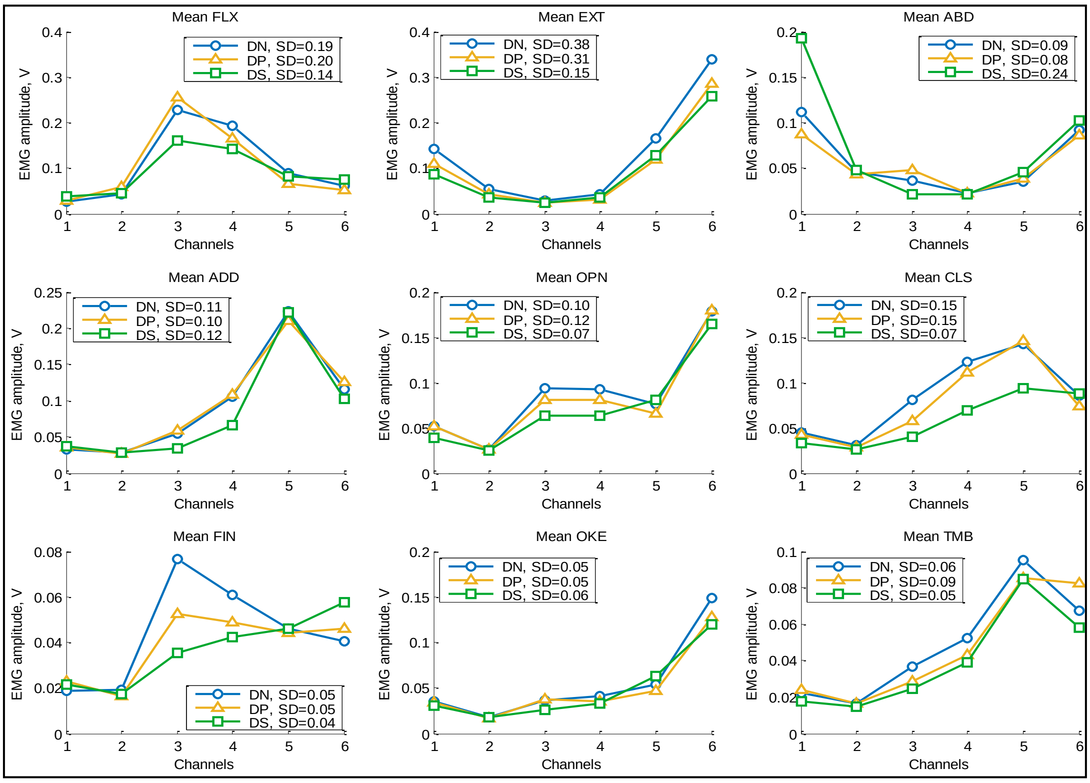
Table 4 - Results of classification attempt during swap of opposite hands. Classification accuracy deteriorates for most gestures, with the exception of EXT. Therefore the LH and RH signals are different and cannot be exchanged

	LH trained, tested with RH data, %			RH trained, tested with LH data, %		
	DN	DP	DS	DN	DP	DS
FLX	50	70	55	60	90	65
EXT	80	75	80	90	85	80
ABD	45	45	80	55	70	80
ADD	55	60	50	60	65	60
OPN	20	20	15	45	35	20
CLS	20	25	10	35	45	20
FIN	50	70	40	40	55	50
OKE	50	15	15	70	25	20
TMB	70	30	65	60	75	60
Mean Accuracy	49	46	46	57	61	51

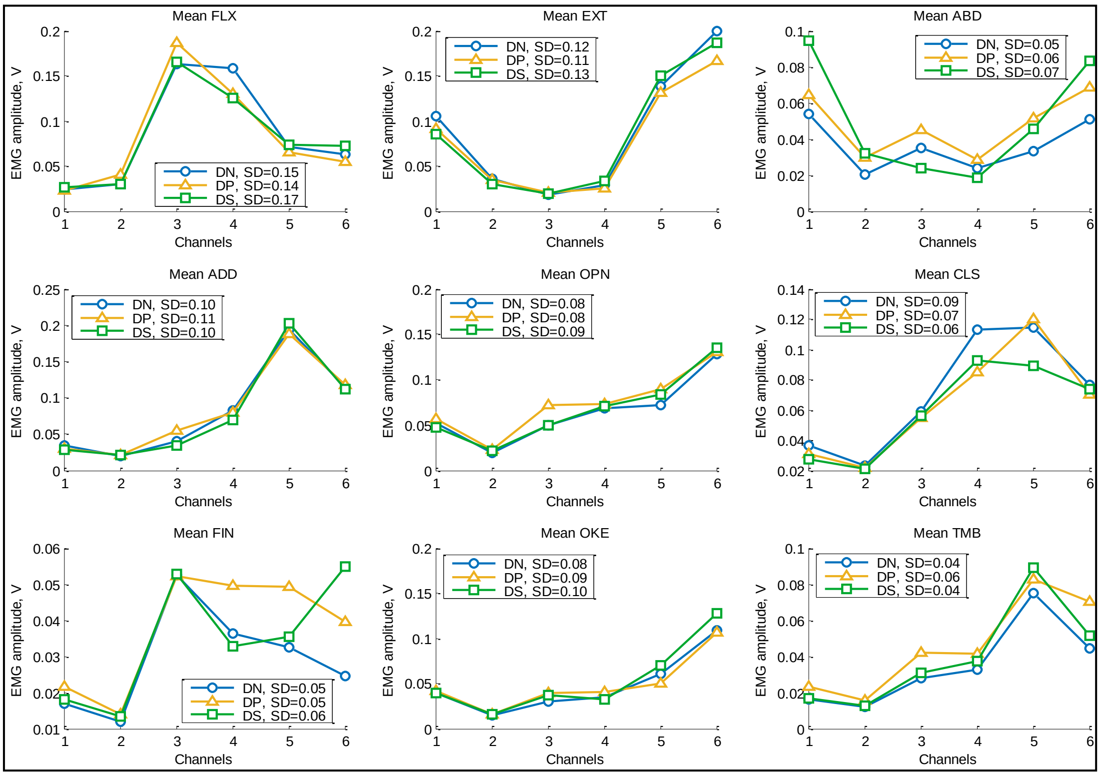
4. Discussion and Conclusion

Due to the attempt to perform zero-retraining, the classification results of all gestures were lower compared to that of individually trained results. This is due to the wide range of subjects with various physiological differences. Remarkably, there is a strong indication of user independence in the DN position of the left hand. Unfortunately this trend does not transcend to the right hand. We also note that all subjects were right-handed, which may have affected the outcome of the left-right hand discrepancies.

Our results show that only the EXT gesture is reliably classifiable across all the variations: 20 subjects, all three rotations and both hands. The experiment has most notably shown that the gestures trained in DN position are distinctively different from those of DP and DS positions. The OPN and CLS gestures was notably the most difficult to classify.



(a)



(b)

Fig. 6 - The 20-subject mean feature extracted gestures of the left hand (a) and (b) right hand across the channels during normal (blue trace), rotation (orange trace) and supination (green trace). The mean amplitude readings in the channels are different across the left and right hand. The inset shows the standard deviation, SD which indicates the variation of the EMG amplitude measured across the six channels for the given gesture

Matsubara et. al [24] reported similarly low classification accuracy of these gestures, however their proposed feature extraction method could increase the classification accuracy from 20% to 60% for the CLS gesture. The works of Khushaba et. al [25] has shown similar trends where classification accuracy is affected by the forearm orientation. Cheng et. al [26] also reported poor classification results ranging from 20% to 60% when the forearm is tested with untrained data. In a similar fashion, Jochumsen et. al [27] acknowledged that intra-class classification accuracies was high, but decreased when more arm positions were added to the training set.

Likewise, the same issues also apply to the LH and RH swap. Therefore in an actual EMG interface, these positions must be accounted for trained separately. In [10], the accuracy among eight subjects registered above 80%. However the classification accuracy dropped to about 25% when performed with test data from the opposite hand. In agreement to the mentioned works, it can be established that the forearm EMG is not hand independent due to the different data distribution. Therefore, the classifier must be made aware of the features extracted from all positions from both hands which unfortunately, is a tedious process to both the user and classifier.

As per objective, we have shown that the major wrist gestures FLX, EXT, ABD and ADD in the DN position had higher classification accuracy. Therefore we recommend these gestures to be considered in the design of zero-retraining EMG. In contrast, the EMG datafield of the finger gestures varies considerably during wrist rotation and hand exchange. The three gestures which are particularly difficult to classify (OPN, CLS, TMB) can be excluded to improve the overall classification accuracy, since the classifier will not be subjected to confusion due to these gestures.

5. Suggestion for Future Works

Our work has shown strong evidence that the gestures in the DN position of the non-dominant hand to have the highest degree of robustness. The procedures were done in the simplest methods from electrode placement to classification, with the intention of mimicking the most careless setup in a practical application. At the hardware front-end, the only conditioning was the 10 – 1000 *Hz* bandpass filter. We also did not perform normalization on the signals. With some additional conditioning like normalization and digital filtering, better results may be achievable.

Acknowledgement

This work was funded by the Malaysian Ministry of Education through the research grant — FRGS/2/2013/SG02/FKP/02/2/F00176.

References

[1] Artemiadis, P. (2012). EMG-based Robot Control Interfaces: Past, Present and Future. In Advances in Robotics & Automation (Vol. 01, pp. 10–12)

[2] Jiang, N., Dosen, S., Muller, K. R., & Farina, D. (2012). Myoelectric control of artificial limbsis there a need to change focus? [In the Spotlight]. IEEE Signal Processing Magazine

[3] Farina, D., & Aszmann, O. (2014). Bionic Limbs: Clinical Reality and Academic Promises. Science Translational Medicine, *6*(257), 6–9

[4] Kumari, P., Mathew, L., & Syal, P. (2017). Increasing Trend of Wearables and Multimodal Interface for Human Activity Monitoring: A Review. Biosensors and Bioelectronics, *90*, 298–307

[5] Watts, P. B., Jensen, R. L., Gannon, E., Kobeinia, R., Maynard, J., & Sansom, J. (2008). Forearm EMG During Rock Climbing Differs from EMG During Handgrip Dynamometry. International journal of exercise science, *1*(1), 4–13

[6] Souissi, H., Zory, R., Bredin, J., & Gerus, P. (2017). Comparison of methodologies to assess muscle co-contraction during gait. Journal of Biomechanics, *57*, 141–145

[7] Herle, S., Man, S., Lazea, G., & Raica, P. (2012). Myoelectric control strategies for a human upper limb prosthesis. Control Engineering and Applied Informatics, *14*(1), 58–66

[8] Yang, D., Yang, W., Huang, Q., & Liu, H. (2017). Classification of Multiple Finger Motions during Dynamic Upper Limb Movements. IEEE Journal of Biomedical and Health Informatics, *21*(1), 134–141

[9] Leijnse, J. . N. A. L., Campbell-Kyureghyan, N. H., Spektor, D., & Quesada, P. M. (2008). Assessment of individual finger muscle activity in the extensor digitorum communis by surface EMG. Journal of neurophysiology, *100*(6), 3225–35

[10] Khushaba, R. N. (2014). Correlation analysis of electromyogram signals for multiuser myoelectric interfaces. IEEE Transactions on Neural Systems and Rehabilitation Engineering, *22*(4), 745–755

[11] Thongpanja, S., Phinyomark, A., Limsakul, C., & Phukpattaranont, P. (2015). A robust measure of probability density function of various noises in electromyography (EMG) signal acquisition. 2015 7th International Conference on Knowledge and Smart Technology (KST), (January 2015), 1–6

[12] Zhang, X., & Zhou, P. (2013). Filtering of surface EMG using ensemble empirical mode decomposition. Medical Engineering and Physics, *35*(4), 537–542

[13] Pylatiuk, C., Müller-Riederer, M., Kargov, A., & Schulz, S. (2009). Comparison of Surface Monitoring Electrodes for Long Term Use in Rehabilitation Device Control. In 2009 IEEE 11th International Conference on Rehabilitation Robotics (pp. 300–304)

[14] Barański, R. (2019). Stability of the EMG signal level within a six-day measuring cycle. In Advances in Intelligent Systems and Computing (831st ed., pp. 125–137). Springer

[15] Phinyomark, A., Quaine, F., Charbonnier, S., Serviere, C., Tarpin-Bernard, F., & Laurillau, Y. (2013). EMG feature evaluation for improving myoelectric pattern recognition robustness. Expert Systems with Applications, *40*(12), 4832–4840

[16] Liu, J., Sheng, X., Zhang, D., Jiang, N., & Zhu, X. (2016). Towards Zero Retraining for Myoelectric Control Based on Common Model Component Analysis. IEEE Transactions on Neural Systems and Rehabilitation Engineering, *24*(4), 444–454

[17] Wahid, M. F., Tafreshi, R., Al-Sowaidi, M., & Langari, R. (2018). Subject-independent hand gesture recognition using normalization and machine learning algorithms. Journal of Computational Science, *27*, 69–76

[18] Samadani, A. A., & Kulic, D. (2014). Hand gesture recognition based on surface electromyography. 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014, 4196–4199

[19] Saponas, T. S., Tan, D. S., Morris, D., Balakrishnan, R., Turner, J., & Landay, J. A. (2009). Enabling always-available input with muscle-computer interfaces. UIST 2009 - Proceedings of the 22nd Annual ACM Symposium on User Interface Software and Technology, 167–176

[20] Stival, F., Michieletto, S., & Pagello, E. (2016). Online subject-independent modeling of sEMG signals for the motion of a single robot joint. Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics, *2016-July*, 1110–1116

[21] Fu, Z., Bani Hashim, A. Y., Jamaludin, Z., & Mohamad, I. S. (2016). Design of a low cost EMG amplifier with discreet op-amps for machine control. ARPN Journal of Engineering and Applied Sciences, *11*(5).

[22] Fu, Z., Bani Hashim, A. Y., Jamaludin, Z., Mohamad, I. S., & Nasir, N. (2017). Optimizing Surface Electromyography Acquisition without Right Leg Drive Circuit. International Journal of Engineering Science Technologies, *1*(1), 13–19

[23] Hargrove, L. J., Li, G., Englehart, K. B., & Hudgins, B. S. (2009). Principal components analysis preprocessing for improved classification accuracies in pattern-recognition-based myoelectric control. IEEE Transactions on Biomedical Engineering, *56*(5), 1407–1414

[24] Matsubara, T., & Morimoto, J. (2013). Bilinear modeling of EMG signals to extract user-independent features for multiuser myoelectric interface. IEEE Transactions on Biomedical Engineering, *60*(8), 2205–2213

[25] Khushaba, R. N., Al-Timemy, A., Kodagoda, S., & Nazarpour, K. (2016). Combined influence of forearm orientation and muscular contraction on EMG pattern recognition. Expert Systems with Applications, *61*, 154–161

[26] Cheng, J., Wei, F., Li, C., Liu, Y., Liu, A., & Chen, X. (2018). Position-independent gesture recognition using sEMG signals via canonical correlation analysis. Computers in Biology and Medicine, *103*, 44–54

[27] Jochumsen, M., Waris, A., & Kamavuako, E. N. (2018). The effect of arm position on classification of hand gestures with intramuscular EMG. Biomedical Signal Processing and Control, *43*, 1–8