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Subject-Independent Hand Gesture Recognition using Normalization and Machine Learning Algorithms

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Highlights

- Generalizability of subject-independent hand gesture recognition were investigated.
- A different strategy to normalize the EMG features was proposed.
- Hand gesture recognition accuracy improved significantly using the proposed normalization strategy.
- The developed approach of gesture recognition will be useful in biomedical application.

Abstract.

Hand gestures can be recognized using the upper limb's electromyography (EMG) that measures the electrical activity of the skeletal muscles. However, generalization of muscle activities for a particular hand gesture is challenging due to between-subject variations in EMG signals. To improve the gesture recognition accuracy without training the machine learning algorithm subject specifically, the time-domain EMG features are normalized to the area under the averaged root mean square curve (AUC-RMS). Results are compared with both original EMG features and EMG features extracted from the signals that are normalized to the maximum peak value. Ten male adult subjects age ranging 20-37 years performed three hand gestures including fist, wave in, and wave out for ten to twelve times. The four basic time domain features including mean absolute value, zero crossing, waveform length, and slope sign change were extracted from the active EMG signals of each channel. Five machine learning algorithms, namely, *k*-Nearest Neighbor (*k*NN), Discriminant Analysis (DA), Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM) were used to classify the three different hand gestures. The results showed that the performance metrics such as accuracy, F1-score, Matthew correlation coefficient, and Kappa score were improved when using the both normalization methods compared to the original EMG features. However, normalization to the AUC-RMS value resulted in substantially more accurate gesture recognition compared to features extracted from signal normalized to maximum peak value using *k*NN, NB, and RF ($p<0.05$). The developed approach

of classifying different hand gestures will be useful in human-computer interaction as well as in controlling devices including prosthesis, virtual objects, and wheelchair.

1 Introduction

Electromyography (EMG) can measure muscles' electrical activities. EMG can be used in various biomedical applications, such as clinical diagnosis, controlling prosthetic or exoskeleton devices, and functional electrical stimulations. The surface EMG sensors have become popular in recent years as they are easy to use, inexpensive, non-invasive, and can be used for recognizing neuromuscular activity preceding the actual movement [1, 2]. However, processing and classifying EMG signals are challenging due to EMG's variability resulted from several factors including anatomical and physiological properties of muscles, level of [3] contraction, dynamic or static muscle states, fatigue, electrode location, sweat from skin, and inherent noises [4, 5]. One common approach to overcome the issues of electrode's shift is to use multichannel EMG data to encapsulate the overall spatiotemporal patterns of the electrical potentials of a given region [6]. Nonetheless, variations in level of muscle contraction can still affect the gesture recognition accuracy [7].

Classification of hand gestures using surface EMG signals from targeted muscles is a challenging task as the signals can be easily contaminated from crosstalk of surrounding muscles. In addition, repositioning of electrodes in different sessions can change the signal's pattern [8]. Since different hand gestures are the result of the cooperative movement of several muscles, a machine-learning algorithm can be trained to learn and predict the gestures based on those muscle co-activation patterns. In a previous study, Englehart et al. [9] reported that the recognition of multiple hand gestures could be substantially improved using the multichannel-based EMG data as opposed to using the single-channel EMG data. Therefore, multichannel-based wearable devices such as the MYO armband, which comes with eight equi-distanced medical grade stainless steel EMG sensors, may provide substantial advantages in biomedical applications. While attractive results were reported by the previous studies in multiple hand gesture recognition using the MYO armband (> 90% gesture recognition accuracy [10, 11]), the device requires synchronization every time a new user wears it and therefore remains subject specific [12-14].

Normalization of EMG signals are typically performed by computing the ratio of the original feature to the feature that is extracted during isometric maximum voluntary contraction (MVC) of the muscle [15, 16]. However, this approach of normalization requires information from the subject performing the MVC. EMG signals have also been normalized to maximum peak values [16, 17]. Using ten EMG features from both time and frequency domain, Kerber et al. [17] reported 95.64% accuracy in recognizing five hand gestures when the signal was normalized to maximum peak value. To achieve greater applicability of gesture-based interfaces, it is essential to develop a generic algoirthm that is subject as well as session independent to facilitate direct deployment of the system without any offline training [18]. In an attempt to develop a subject independent algorithm for gesture recognition, Matsubara and Morimoto [19] used bilinear modelling of EMG signals to train a support vector machine (SVM) algorithm and reported 73% of overall accuracy in recognizing different hand motions. While several studies were able to produce great success in recognizing multiple hand gestures by training the machine learning on each subject level, development of an efficient and accurate gesture recognition algorithm that is not subject specific remains challenging.

The aim of this study is to investigate the generalizability of subject-independent hand gesture recognition using different machine learning algorithms that are trained upon EMG features normalized to muscle contraction level. Since the muscle contraction level usually varies both between and within the subjects for the same gesture, we hypothesize that normalizing the EMG features to the energy of muscle contraction for a given gesture would substantially improve the machine learning performance in recognizing different hand gestures. The results will be compared with the gesture recognition accuracy using the original EMG features as well as using the features obtained from normalized EMG signal to maximum peak value.

2 Methods

2.1 Experimental protocol

The forearm's EMG data of ten healthy male subjects age ranging from 20 to 37 years old were acquired using a MYO armband (Fig. 1a), a commercially available device that includes eight equidistance EMG sensors [20]. The MYO armband was placed at approximately the same location of the subject's forearm such that the fourth sensor is located at the mid of flexor carpi radialis (see Fig. 1c). Each subject performed three different hand gestures including fist, wave in, and wave out ten to twelve times (see Fig. 1b). Approval for the study was obtained from the Institutional Review Board (IRB) and written informed consent was provided according to the

Board's guideline. The EMG data—unitless 8 bit unsigned integer values, resulting from a proprietary conversion algorithm from mV [21]—were sampled at 200Hz and directly streamed to the Matlab's workspace using a custom-written script via Bluetooth communication. Sample EMG signals from all eight channels during performing all three hand gestures are shown in Fig. 2.

Figure 1 and 2 about here

2.2 Data segmentation

In the present study, the muscle onset was defined as the region where the EMG values were higher than the baseline (first 0.5 second of EMG data) plus one standard deviation of the baseline. We further computed the root mean square (RMS) curve for the average of eight EMG signals (Fig. 3a) using 300ms sliding window with 50% overlap. The area under the curve (AUC) value for each trial during the muscle onset period was also computed (hatched region in Fig. 3b).

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}\,, \tag{1}$$

where N is the sliding window size, and $\boldsymbol{x_n}$ is the EMG signal at the n-th data point.

Figure 3 about here

2.3 Feature extraction

Four basic time domain features including mean absolute value (MAV), zero crossing (ZC), waveform length (WL), and slope sign change (SSC) were extracted from the muscle onset region of each channel according to Equations 2-5 (between the green vertical lines in Fig. 3). Therefore, each gesture would form a feature vector of 32 values (4 EMG features × 8 channels). These features were shown to be robust for classification of EMG signals compared to the feature sets extracted using the short-time Fourier transform, the wavelet transform, and the wavelet packet transform [1, 22, 23].

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n| \tag{2}$$

$$ZC = \sum_{n=1}^{N-1}[sign(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq 0], \qquad sign(x) = \begin{cases} 1 & ,x \geq 0 \\ 0 & ,x < 0 \end{cases} \tag{3}$$

$$WL = \sum_{n=1}^{N-1}|x_{n+1} - x_n| \tag{4}$$

$$SSC = \sum_{n=2}^{N-1} f[(x_n - x_{n-1}) \times (x_n - x_{n+1})], \; f(x) = \begin{cases} 1 & ,x \geq 0 \\ 0 & ,x < 0 \end{cases} \tag{5}$$

where N is the length of the muscle onset, and $\boldsymbol{x_n}$ is the EMG signal at the n-th data point.

2.4 Data normalization

All EMG features were normalized by the area under the root mean square curve (AUC-RMS) value:

$$X_{norm} = \frac{X_{original}}{AUC_{RMS}}, \tag{6}$$

where X represents the EMG feature and AUC_{RMS} represents the area under the RMS curve which was computed using the sliding window approach on the averaged EMG signal. EMG features were also computed from the normalized EMG signal according to the previous study [17].

2.5 Machine learning

Five machine learning algorithms including *k*-nearest neighbor (KNN), Discriminant Analysis (DA), Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM) were used to classify the three different hand gestures [24]. A matrix of features was formed by accumulating the values of MAV, ZC, WL, and SSC from each channel of the MYO armband for all subjects and trials. The rows of matrix include all the gestures trials for all subjects (number of gestures × trials × subject), and columns are EMG features for all channels (EMG features × number of channels). The machine learning algorithms were applied on features without normalization, features extracted from normalized EMG signal, and features normalized to the AUC-RMS values. Each classifiers' internal parameters were optimized using the grid search method and the final parameters are given in Table 2. To measure the subject-independent machine learning performance, a cross-validation approach was employed where data from eight subjects were used for training and two subjects for testing. This resulted in a total of ${}^{10}C_2$ (i.e., a total of 45 combinations) classification outcomes for each machine learning algorithm. The performance is evaluated by the overall mean accuracy, F1-score, Kappa, and Matthew's Correlation Coefficient (MCC) [25, 26]. The F1-score demonstrates the balance between the precision and sensitivity and can be zero when either the precision or the sensitivity is zero. The MCC shows the correlation between the observed and predicted classifications. The value of one for MCC represents a perfect prediction. Kappa measurement demonstrates the level of accuracy that would be generated purely by chance. A value of one indicates perfect accordance of the model prediction and the actual classes.

2.6 Statistical Analysis

The normalcy of the accuracy distribution was tested using the *Lilliefors* test, which is a statistical test for a null hypothesis that data come from a normally distributed population. As the data distribution was found to be non-normal, a non-parametric *Wilcoxon signed-rank* test, an alternative to parametric Student's *t*-test, was used to compare the classification accuracies between the normalization strategies. The level of significance was set at $p<0.05$. All statistical calculations were performed using Matlab.

3 Results

The overall classification accuracies were higher for all five machine learning algorithms including KNN, DA, NB, RF, and SVM when using the normalized EMG features to the AUC-RMS value compared to using both original EMG features and features obtained from normalized EMG signal to the maximum peak value (Table 1). The RF algorithm yielded the highest classification accuracy using EMG features normalized to the AUC-RMS value (96.38%) whereas the DA algorithm produced better results for both original EMG features (94.54%) and normalization to peak value approach (95.25%). Other performance metrics such as F1-score, MCC, and Kappa scores were found to be consistently higher when using the proposed normalization approach compared to using both the original data and normalization to maximum peak value approach (Table 1). The accuracy distributions for all the classifiers were found to be closer to the mean values when using the proposed normalization approach compared to both original data and normalization to peak value approach (i.e., low standard deviation). These results indicated that the between-subject differences in the EMG features were reduced when using the proposed normalization technique for which the machine-learning algorithms produced lower variances in the validation stage.

As can be seen in Fig. 4, which presents confusion matrices, in most cases the prediction accuracies for each hand gesture including fist, wave-in, and wave-out were found to be higher when using the proposed normalization approach compared to using the original data or normalization to peak value approach. The last column of the confusion matrices shows the prediction accuracies of the algorithms whereas the last row shows the percentage of accurately identified gestures. The diagonal end-cell represents the overall classification accuracy of the algorithm(s).

The results showed that all the machine-learning techniques were able to predict both wave in and wave out hand gestures with greater than 89% accuracy using both original and normalized data. Among the gestures, the prediction accuracy was the most accurate for the wave-out gesture (original EMG feature: 94.6-99.5%, normalized to peak approach: 93.1-99.6%, and normalized to AUC-RMS approach: 95.2-100%) and least accurate for the fist gesture (original EMG feature: 66.3-92.8%, normalized to peak approach: 67.5-94.7%, and normalized to AUC-RMS approach: 78.90-96.6%) (see Fig. 4 end column).

Figure 4 about here

The distribution of the classification accuracies for all machine learning algorithms were found to be skewed to the left. Before comparing the mean differences between the two normalization approaches, a normality check was conducted on the accuracy distribution using the Lilliefors test which showed that none of the distributions were normal ($p<0.01$). Therefore, a non-parametric Wilcoxon signed-rank test was used to compare the machine learning accuracies when using features obtained from normalized EMG signal to the maximum peak value and features normalized to AUC-RMS value. Results showed that the overall prediction accuracy using the proposed normalization approach was significantly higher when using kNN, NB, and RF compared to both original features and features obtained from normalized EMG signal to maximum peak value ($p<0.01$). However, the accuracy differences between the normalization methods for both DA and SVM were not significant.

4 Discussion

The aim of this study was to investigate the generalizability of subject-independent hand gesture recognition using machine learning algorithms by normalizing the time domain EMG features to the energy of muscle contraction, i.e., area under the root mean square curve (AUC-RMS). In addition, the gesture recognition performances due to using the original EMG features, features obtained from normalized EMG signal to maximum peak value, and EMG features normalized to AUC-RMS value were compared. Results showed that the prediction accuracy of the machine learning algorithms were increased when the data were normalized using the proposed strategy compared to both using the original data and normalization to peak value approach. The maximum accuracy was found for RF algorithm when using the proposed normalization method (96.38%) and the least accuracy was obtained when using the original data with the NB algorithm (81.76%). A non-parametric Wilcoxon signed-rank test for mean differences between the accuracies from both normalization approaches showed that the increment of the overall accuracy for kNN, NB, and RF by 1.63-6.43% with the proposed normalization strategy were not by chance ($p<0.01$). Other performance metrics including F1-score, MCC, and Kappa scores also demonstrated the superiority of the proposed normalization approach compared to both original data and data from normalization to maximum peak value approach (Table 1).

Surface EMG signal has potentials in a wide range of applications as it can be easily acquired using simple, inexpensive, and non-invasive sensors. However, most EMG-based algorithms are subject-specific due to inherent complex pattern of the signal influenced by both anatomical and physiological properties of the muscles, level of contraction, dynamic muscle states, fatigue, electrode location, and sweat from skin. These differences may create a wide range of EMG feature values for the same hand gesture and consequently degrade the machine learning performance. The capacity of efficiently training the machine-learning algorithms prior to deploying in a system has greater applications in controlling prosthetic devices, human-assisting manipulators, and sign language recognition [19, 27]. The present study showed that the gesture detection accuracy can be substantially improved without any subject-specific training when the EMG features were normalized to the AUC-RMS value (Fig. 4).

Previous studies have reported over 90% accuracies in recognizing different hand gestures by training the machine learning algorithms in a subject specific manner (see [10, 11, 28]). However, these accuracies dropped below 80% when the machine learning algorithms were trained subject-independently [18, 19]. For example, Georgi et al. [18] reported 74.3% recognition accuracy using Hidden Markov Models (HMM) to classify a total of twelve gestures; and Samadani and Kulic [29] reported 79% accuracy using an HMM to classify a total of ten gestures. While in a recent study, Kerber et al. [17] reported an overall classification accuracy of 95.64% for five hand gestures using the normalization to maximum peak value approach, the authors used a total of ten features in their study and did not reported the individual gesture prediction accuracy. Although the present study used only three hand gestures, the greater success of each gesture recognition, i.e., fist, wave in, and wave out, by the RF algorithm (>95%) with overall mean accuracy of 96.4% (median 97.73%) could provide the foundation for future studies with larger number of subjects and gestures. The presented approach of generalizing the muscle activation pattern for a specific hand gestures across the subjects will provide greater applicability in controlling the prosthetic devices.

The results from the confusion matrices in Fig. 4 indicated that both wave in and wave out gestures were more distinctive in nature compared to the fist gesture. All machine learning algorithms were able to predict wave in and wave out gestures with accuracy ranging from 89-100% whereas the prediction accuracy for the fist gesture ranged from 66.3 to 96.6%. The lower recognition rate for the fist gesture by all machine learning algorithms may be explained by the complex muscle activity of several intrinsic muscles during the fist gesture that are connected to the finger bones via long tendons as opposed to the extrinsic muscles that supports the large wrist movement as appearing in wave in and wave out [30]. The fist gesture was found to be mostly confounded with the wave in gesture which most likely occurred because fingers are moving in the same direction while performing both of these gestures. This was also observed in a previous study where the fist gesture was found to be confounded with the wave-in gesture [28]. Overall, the results indicated that the EMG features used in the present study may be inadequate to accurately capture the differences in muscle activation patterns between fist and wave in gestures. In a future study, robust machine learning algorithms using more EMG features such as autoregressive coefficients, Cepstral coefficients, and Willison amplitude will be used to investigate whether the 'fist' gesture recognition accuracy can be improved.

Despite having many advantages, the proposed approach has a number of limitations that should be considered. First, the total number of subjects was relatively small in this study. However, a large number of trials (10-12) for each subject was used to increase the sample size for the machine learning. Furthermore, a cross-fold approach was used to estimate the true performance of the machine learning which reduced the possibility of overfitting. Second, a global thresholding strategy was utilized for the muscle onset detection which may be unsuitable for the EMG signal from all channels as not all muscles get activated at the same time. A local thresholding technique may improve the detection of precise muscle onset region and consequently the performance of the machine learning may be improved further. Finally, only three hand gestures were investigated in this study. While the machine learning strategies may be able to detect these hand gestures with greater accuracy, the purpose of this study was to determine the effectiveness of the proposed normalization technique. Since, the efficacy of the proposed normalization in generalizing the muscle activation pattern in both between and within subjects has been shown in this study, different complex hand gestures will be investigated in the future study.

5 Conclusion

This paper investigated the machine learning performance in recognizing three different hand gestures including fist, wave in, and wave out subject independently, and proposed a strategy to improve the gesture recognition accuracy. A non-parametric Wilcoxon signed-rank test was used to compare the gesture recognition accuracies between the two groups, i.e., accuracies obtained using the normalization to maximum peak value approach and accuracies obtained using the normalization to AUC-RMS value approach. Results showed that the classification accuracies were higher when using the proposed normalization strategy compared to both original features and features obtained from normalization to maximum peak value approach. Among the classifiers, the RF algorithm obtained a maximum gesture recognition accuracy of 96.4% using the features normalized to AUC-RMS value. The proposed normalization approach may be useful in diverse biomedical applications, including designing control functions for prosthetic devices, exoskeleton, and human computer interface.

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References

[1] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering,* vol. 50, pp. 848-854, 2003.

[2] M. Vaiman, "Standardization of surface electromyography utilized to evaluate patients with dysphagia," *Head & face medicine,* vol. 3, p. 26, 2007.

[3] R. H. Chowdhury, M. B. Reaz, M. A. B. M. Ali, A. A. Bakar, K. Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques," *Sensors,* vol. 13, pp. 12431-12466, 2013.

[4] M. B. Reaz, M. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: detection, processing, classification and applications," *Biological procedures online,* vol. 8, pp. 11-35, 2006.

[5] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. A. A. Bakar, K. Chellappan, and T. G. Chang, "Surface Electromyography Signal Processing and Classification Techniques," *Sensors (Basel, Switzerland),* vol. 13, pp. 12431-12466, 2013.

[6] Y. Du, W. Jin, W. Wei, Y. Hu, and W. Geng, "Surface EMG-Based Inter-Session Gesture Recognition Enhanced by Deep Domain Adaptation," *Sensors (Basel, Switzerland),* vol. 17, p. 458, 2017.

[7] M. Jordanić, M. Rojas-Martínez, M. A. Mañanas, J. F. Alonso, and H. R. Marateb, "A Novel Spatial Feature for the Identification of Motor Tasks Using High-Density Electromyography," *Sensors,* vol. 17, p. 1597, 2017.

[8] P. Geethanjali and K. Ray, "Identification of motion from multi-channel EMG signals for control of prosthetic hand," *Australasian physical & engineering sciences in medicine,* vol. 34, pp. 419-427, 2011.

[9] K. Englehart, B. Hudgin, and P. A. Parker, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering,* vol. 48, pp. 302-311, 2001.

[10] F. Bian, R. Li, and P. Liang, "SVM based simultaneous hand movements classification using sEMG signals," in *Mechatronics and Automation (ICMA), 2017 IEEE International Conference on*, 2017, pp. 427-432.

[11] I. Donovan, K. Valenzuela, A. Ortiz, S. Dusheyko, H. Jiang, K. Okada, and X. Zhang, "MyoHMI: A low-cost and flexible platform for developing real-time human machine interface for myoelectric controlled applications," in *Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on*, 2016, pp. 004495-004500.

[12] S. Shin, R. Langari, and R. Tafreshi, "A performance comparison of emg classification methods for hand and finger motion," in *ASME 2014 Dynamic Systems and Control Conference*, 2014, pp. V002T16A008-V002T16A008.

[13] S. Shin, R. Tafreshi, and R. Langari, "Robustness of Using Dynamic Motions and Template Matching to the Limb Position Effect in Myoelectric Classification," *Journal of Dynamic Systems, Measurement, and Control,* vol. 138, p. 111009, 2016.

[14] S. Shin, R. Tafreshi, and R. Langari, "Myoelectric pattern recognition using dynamic motions with limb position changes," in *American Control Conference (ACC), 2016*, 2016, pp. 4901-4906.

[15] G. J. Lehman and S. M. McGill, "The importance of normalization in the interpretation of surface electromyography: a proof of principle," *Journal of manipulative and physiological therapeutics,* vol. 22, pp. 444-446, 1999.
[16] M. Halaki and K. Ginn, "Normalization of EMG signals: To normalize or not to normalize and what to normalize to?," in *Computational intelligence in electromyography analysis-a perspective on current applications and future challenges*, ed: InTech, 2012.
[17] F. Kerber, M. Puhl, and A. Krüger, "User-independent real-time hand gesture recognition based on surface electromyography," in *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services*, 2017, p. 36.
[18] M. Georgi, C. Amma, and T. Schultz, "Recognizing Hand and Finger Gestures with IMU based Motion and EMG based Muscle Activity Sensing," in *BIOSIGNALS*, 2015, pp. 99-108.
[19] T. Matsubara and J. Morimoto, "Bilinear modeling of EMG signals to extract user-independent features for multiuser myoelectric interface," *IEEE Transactions on Biomedical Engineering,* vol. 60, pp. 2205-2213, 2013.
[20] Thalmic Labs. 2013. Available: https://www.myo.com/. (Accessed on: Nov 1, 2017).
[21] I. H. Robô, "Gesture Spotting from IMU and EMG Data for Human-Robot Interaction," Universidade de Coimbra, 2016.
[22] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Transactions on Biomedical Engineering,* vol. 55, pp. 1956-1965, 2008.
[23] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering,* vol. 40, pp. 82-94, 1993.
[24] S. Marsland, *Machine learning: an algorithmic perspective*: CRC press, 2015.
[25] J. Akosa, "Predictive Accuracy: A Misleading Performance Measure for Highly Imbalanced Data," in *Proceedings of the SAS Global Forum*, 2017.
[26] D. M. Powers, "Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation," 2011.
[27] M. R. Ison and P. Artemiadis, "Beyond user-specificity for EMG decoding using multiresolution muscle synergy analysis," in *Dynamic Systems and Control Conference*, 2013.
[28] M. E. Benalcázar, A. G. Jaramillo, A. Zea, A. Páez, and V. H. Andaluz, "Hand gesture recognition using machine learning and the Myo armband," in *Signal Processing Conference (EUSIPCO), 2017 25th European*, 2017, pp. 1040-1044.
[29] A.-A. Samadani and D. Kulic, "Hand gesture recognition based on surface electromyography," in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, 2014, pp. 4196-4199.
[30] A. A. Adewuyi, L. J. Hargrove, and T. A. Kuiken, "An Analysis of Intrinsic and Extrinsic Hand Muscle EMG for Improved Pattern Recognition Control," *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society,* vol. 24, pp. 485-494, 2016.
[31] K. T. Patton, *Anatomy and Physiology*: Elsevier Health Sciences, 2015.

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Figure captions

Fig 1: (a) A MYO armband showing the sensor sequences, (b) three hand gestures including fist, wave in, and wave out (left to right) [20], (c) anterior view of forearm's muscles [31]

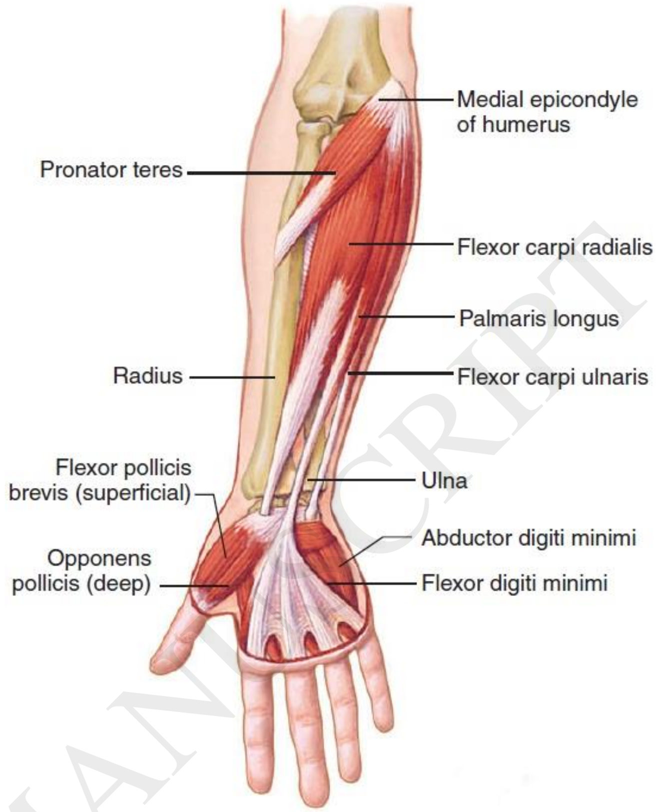
Fig 2: Sample EMG signals from all eight channels of MYO armband while performing three different hand gestures (a) fist, (b) wave in, and (c) wave out

Fig 3: (a) An example of average EMG signal computed from all eight channels where green vertical lines show the segmented region which are above the threshold value, (b) the RMS curve for the averaged EMG signal where the hatched region represents the AUC-RMS

Fig 4: Confusion matrices for the machine learning algorithms (a) *k*-nearest neighbor (*k*NN), (b) Discriminant Analysis (DA), (c) Naïve Bayes (NB), (d) Random Forest (RF), and (e) Support Vector Machine (SVM). OR, original EMG features; NP, EMG signal normalized to maximum peak value; and NA, EMG features normalized to area under the RMS curve.

Figure 1

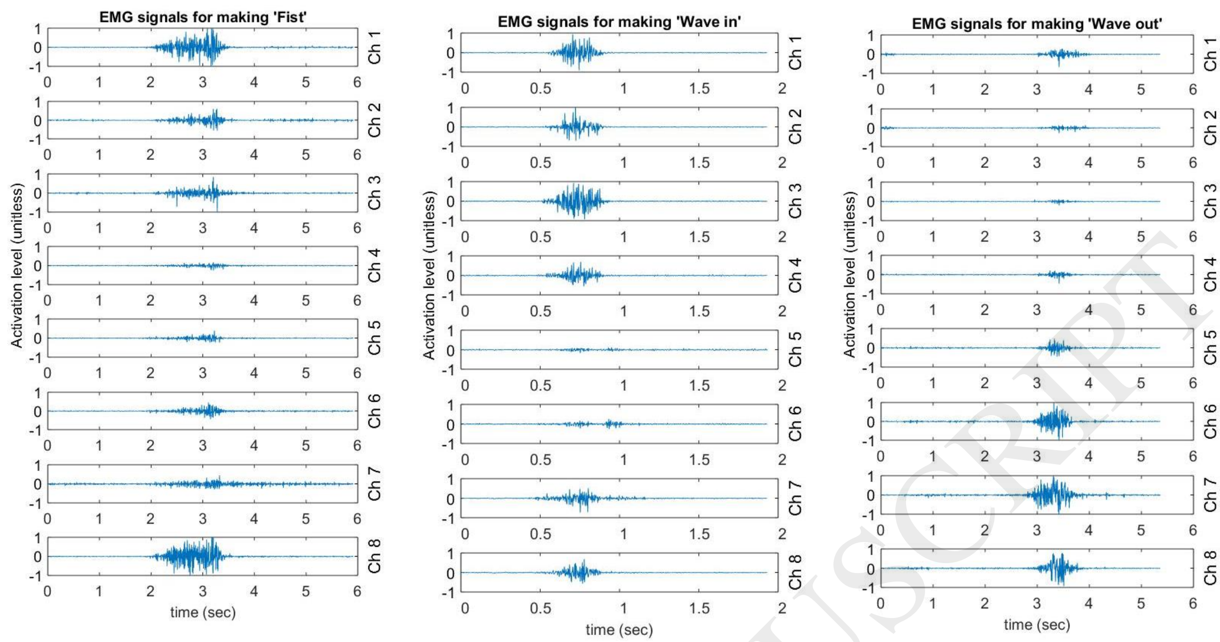
(a)


Medial epicondyle
of humerus
Pronator teres
Flexor carpi radialis
Palmaris longus
Radius
Flexor carpi ulnaris
Flexor pollicis
brevis (superficial)
Ulna
Abductor digiti minimi
Opponens
pollicis (deep)
Flexor digiti minimi

(b)

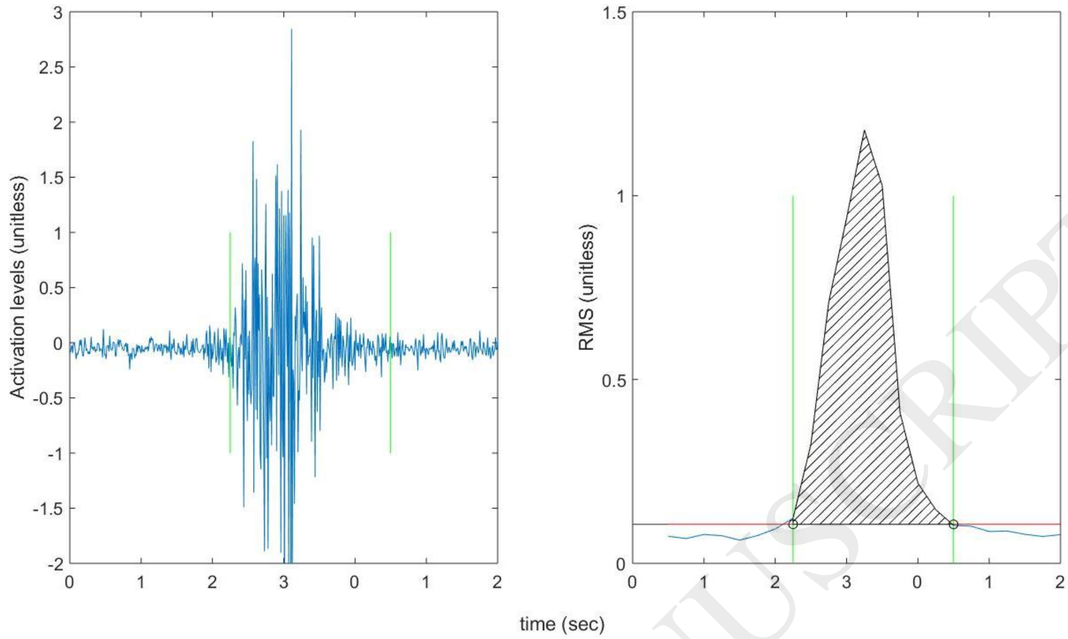
(c)

Figure 2


EMG signals for making 'Fist'
EMG signals for making 'Wave in'
EMG signals for making 'Wave out'
Activation level (unitless)
time (sec)
Ch 1
Ch 2
Ch 3
Ch 4
Ch 5
Ch 6
Ch 7
Ch 8

(a) (b) (c)

Figure 3


Activation levels (unitless)
RMS (unitless)
time (sec)
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
1
2
3
0
1
2

(a) (b)

Figure 4

Output class		Fist	Wave in	Wave out	
Fist	OR	3297	435	78	86.50%
	NP	3300	314	89	89.10%
	NA	3536	511	9	87.20%
Wave in	OR	337	3612	19	91.00%
	NP	275	3722	14	92.80%
	NA	205	3596	6	94.50%
Wave out	OR	146	93	4187	94.60%
	NP	205	104	4181	93.10%
	NA	39	33	4269	98.30%
	OR	87.20%	87.20%	97.70%	**90.90%**
	NP	87.30%	89.90%	97.60%	**91.80%**
	NA	93.50%	86.90%	99.60%	**93.40%**

Target Class

(a)

Output class		Fist	Wave in	Wave out	
Fist	OR	3390	263	0	92.80%
	NP	3392	193	0	94.60%
	NA	3422	211	0	94.20%
Wave in	OR	369	3877	0	91.30%
	NP	374	3945	0	91.30%
	NA	354	3929	0	91.70%
Wave ou	OR	21	0	4284	99.50%
	NP	14	2	4284	99.60%
	NA	4	0	4284	99.90%
	OR	89.70%	93.60%	100%	**94.60%**
	NP	89.70%	95.30%	100%	**95.20%**
	NA	90.50%	94.90%	100%	**95.30%**

Target Class

(b)

Output class		Fist	Wave in	Wave out	
Fist	OR	3318	983	703	66.30%
	NP	3501	1000	689	67.50%
	NA	3458	705	218	78.90%
Wave in	OR	359	3144	1	89.70%
	NP	199	3112	1	94.00%
	NA	322	3435	0	91.40%
Wave ou	OR	103	13	3580	96.90%
	NP	80	28	3594	97.10%
	NA	0	0	4066	100.00%
	OR	87.80%	75.90%	83.60%	**82.30%**
	NP	92.60%	75.20%	83.90%	**83.60%**
	NA	91.50%	83%	94.90%	**89.80%**

Target Class

(c)

Output class		Fist	Wave in	Wave out	
Fist	OR	3435	690	111	81.10%
	NP	3466	614	59	83.70%
	NA	3640	89	39	96.60%
Wave in	OR	271	3410	41	91.60%
	NP	244	3349	25	93.10%
	NA	30	3950	70	97.50%
Wave out	OR	74	40	4132	97.30%
	NP	90	177	4200	94.00%
	NA	110	101	4175	95.20%
	OR	90.90%	82.40%	96.50%	**89.90%**
	NP	91.70%	80.90%	98%	**90.30%**
	NA	96.30%	95.40%	97.50%	**96.40%**

Target Class

(d)

Output class		Fist	Wave in	Wave out	
Fist	OR	3519	218	96	91.80%
	NP	3503	189	6	94.70%
	NA	3427	221	1	93.90%
Wave in	OR	208	3884	72	93.30%
	NP	174	3894	118	93.00%
	NA	344	3916	0	91.90%
Wave out	OR	53	38	4126	97.80%
	NP	103	58	4160	96.30%
	NA	9	3	4283	99.70%
	OR	93.10%	93.80%	96.10%	**94.40%**
	NP	92.70%	94%	97.10%	**94.70%**
	NA	90.70%	94.60%	100%	**95.30%**

Target Class

(e)

Table 1: Classification accuracies using original EMG features, features obtained from normalized EMG signal to the maximum peak value, and features normalized to AUC-RMS value. EMG, electromyography; *k*NN, k Nearest Neighbor; DA, Discriminant Analysis; NB, Naïve Bayes; RF, Random Forest; SVM, Support Vector Machine; MCC, Matthew's correlation coefficient.

Machine learning	Mean				Std				F1-score				MCC				Kappa				P-value for normalization accuracies
	Original	Norm to peak	Norm to area		Original	Norm to peak	Norm to area		Original	Norm to peak	Norm to area		Original	Norm to peak	Norm to area		Original	Norm to peak	Norm to area		

kNN	90.54	91.46	93.08		6.33	5.53	5.30		0.91	0.91	0.93		0.86	0.87	0.90		0.80	0.81	0.85	<0.01
DA	94.54	95.20	95.25		5.20	4.59	3.79		0.94	0.95	0.95		0.92	0.93	0.93		0.88	0.89	0.90	0.88
NB	81.76	83.21	89.62		9.59	9.24	8.08		0.83	0.83	0.90		0.75	0.76	0.85		0.60	0.62	0.77	<0.01
RF	89.92	89.95	96.38		6.96	6.08	4.49		0.90	0.90	0.96		0.85	0.85	0.95		0.77	0.78	0.92	<0.01
SVM	93.99	94.48	94.96		5.82	5.21	4.69		0.94	0.95	0.95		0.92	0.92	0.93		0.87	0.88	0.89	0.25

Table 2: Tuning parameters for the machine learning algorithms.

Tuning parameters	Original	Normalized to peak	Normalized to area	Searching range
kNN	Neighbor: 3	Neighbor: 5	Neighbor: 3	1-15
DA	Discriminant Type: Linear	Discriminant Type: Linear	Discriminant Type: Linear	linear, quadratic, diagquadratic
NB	Distribution: Kernel	Distribution: Kernel	Distribution: Kernel	kernel, multinomial, normal
RF	Trees: 350	Trees: 500	Trees: 275	50-500
SVM	Box: 0.5, Ker: 7	Box: 7, Ker: 7	Box: 15, Ker: 11	0.01-100