Improved Robustness of EMG Pattern Recognition for Transradial Amputees with EMG features against Force Level Variations

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***Abstract*—Feature extraction is an essential process for removing the unwanted part and interference of the Electromyography (EMG) signal, and to extract the useful information hidden in it. Inorder to obtain high performance of Myoelectric Control (MEC), the choice of features plays an important role. The studies carried out earlier to overcome force level variation have used features which are redundant, affecting the robustness and the classification performance. This study's main objective is to assess a database's performance consisting of nine upper limb amputee subjects with EMG data recorded at three different force levels when six motions were classified using twenty different time domain features that are frequently found in the literature. Training is carried out at one force level, and the other two unknown force levels are used for testing. Out of the twenty features, the one that is the most stable is displayed for each force level. The results show that root mean square (RMS) feature outperformed other features for training at low and medium force levels, and Wilson amplitude (WAMP) feature for training at a high force level, when compared with the most widely used linear discriminant analysis (LDA) classifier. The average classification accuracy for the nine amputee subjects trained with the RMS feature at low and medium force levels was 42% and 51.78% percent, respectively. For high force level, when trained using WAMP feature, an accuracy of 46.78% has been obtained. The features are verified using histogram plots. This study will help select those features which are not important for robust classification of hand movements.**

***Index Terms*—force level variations, feature extraction, robust classification, upper limb amputees, myoelectric control**

I. Introduction

There is a fast improvement in the field of upper limb prosthesis due to sensors, motors, digital controllers, and rapid fabrication and prototyping [1]–[3]. The primary source of control for electrically powered prostheses is the Electromyography (EMG) signal, and this control is referred to as Myoelectric Control (MEC). The subject's intended movement is classified with the help of Pattern Recognition (PR) scheme, where a set of features from the EMG signal for a movement is extracted and given to the classifier for making the decision [4].

Myoelectric control is used for discriminating patterns of EMG signals generated at different hand movements. For each action, a unique pattern of EMG signal is created, and this is used as a control command in the myoelectric controller [5]. The various steps in MEC based PR are a) Pre-processing; b) Feature Extraction; and c) Classification. Useful information hidden in the signal is only extracted via feature extraction, which removes the undesirable portions of the signal. Three crucial characteristics are anticipated for the features that were derived from the EMG signal. Maximum class separability, noise resistance, and low complexity are the three criteria. Studies have demonstrated that feature redundancy has an impact on classification accuracy [6], [7].

The major challenge is to use a prosthetic hand with the same degree of freedom as a biological hand [8], [9]. EMG signal is extracted from the stump of the amputee to extract movement commands. There are numerous restrictions on the techniques created in the ideal laboratory environment. However, research so far has been predominantly directed to obtain high accuracy in a laboratory setting rather than encountering the practical factors that affects the algorithm performance during the clinical application of PR. During daily life activities, the classification performance of the PR changes. This change is mainly due to the variation in force level, wrist orientation, muscle fatigue, limb position, and so on. Many research works in the literature have made efforts towards tackling this problem [10], [11]. The effects of force variation have been highlighted in some recent works [12], [13]. The data used for training is derived from one or more force levels, and when tested at a different force level, the accuracy of classification during training varies greatly. Few studies have looked at the effects of force variation, and those that have mainly examined the method's effectiveness on healthy people rather than amputees. Daily activities involving different force levels alter the time-frequency and probability function properties, which results in alterations to the EMG pattern. This variation will degrade the classification performance during the practical use [14]–[16].

Many studies evaluated the EMG classification performance on healthy participants rather than on amputees and employed a variety of training techniques to mitigate force variation. Generalization of results of earlier work carried on healthy subjects is not known on amputee subjects, and this is due to the change in muscle structure after amputation. This will lengthen the training period and restrict the use in clinical settings. Hence, the main aim here was to perform a study on the invariant features against force level variations on amputee subjects. This will help in making the PR robust

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and reduce the training time. The frequency domain, time domain, or time-frequency domain are all possible EMG feature representations. The former are used in this context since they don't need to be transformed, unlike the frequency domain characteristics, which do. Additionally, this reduces MEC's total computational complexity. This facilitates real-time implementation while having little impact on classification accuracy.

The aim of this study is to examine how varying force levels affect the performance of MEC and identify features that remain consistent despite these variations. By identifying such features, the robustness of the PR system can be improved. To achieve this goal, a) the EMG dataset from nine amputees has been used, performing six classes of hand motions (here the analysis is carried out on grip and finger movements) at three different force levels, b) Eight channels are used to extract twenty EMG features in the time domain at each force level, c) the performance evaluation is done through histogram plot. The classification performance of the features is evaluated using an LDA classifier with training data from the individual force level and test data from the other two unobserved force levels. The results of this study may be used to select the appropriate time domain properties for an EMG-based PR system in the presence of force level variations.

The paper is organised as follows: Section 2 explains the technique, Section 3 gives the experimental findings and an analysis, and Section 4 gives the paper's conclusion.

II. Methodology

A. Subjects and Data Collection

The Al-Timemy et al. (2016) [12] database was used in this analysis. The EMG signals from nine amputee people between the ages of 19 and 57 constitute the database. Eight Ag/AgCl electrodes from the amputed hand were used to capture the EMG signals.The data were recorded using a specially made multi-channel collection device with a sampling rate of 2 kHz. Al-Timemy et al. (2016) [12] contains the electrode locations and a thorough explanation of the database.

B. Experimental procedure

Six classes of movements were performed: a) thumb flexion (M1), b) index flexion (M2), c) fine pinch (M3), d) tripod grip (M4), e) hook grip (M5) and f) spherical grip (M6). Before beginning the experiment, the subjects were introduced into a training session. Six hand motions were executed by the subject, each with three distinct levels of force (low, medium, and high). During the experiment, participants were tasked with observing electromyography (EMG) signals on a screen with visual feedback from Labview. The amputees had trouble exerting various amounts of force, but were told to visualise making the necessary action with an undamaged hand while exerting the necessary force. Instead of recording the EMG signals at the usual force level used by amputees to operate their prosthetics, the main goal was to imitate force level variation throughout daily use by recording the EMG signals at lower and higher levels of force. The experiment involved three trials for training each movement class, with the remaining two to five trials used to test the classifier. Total number of trials performed = (3 force levels) × (6 actions) × (No of trials for each action).

C. Pre-processing and Segmentation

A Butterworth filter and a 50 Hz notch filter have been used to filter the EMG signals within the 20-450 Hz range and eliminate power line interference, minimising the impact of crosstalk and artefacts caused by electrode movement. The time-series data captured by the sensors have been divided into 200 ms disjointed windows. This window size was selected to ensure real-time decision-making within 300 ms [17], [18].

D. Feature Extraction

The feature vector is a concise representation of the features extracted from raw EMG data. This process is essential because it assists in extracting relevant information for the classifier while simultaneously reducing the impact of noise in the data. Three groups are used to categorise the features: time domain, frequency domain, and time-frequency domain. Time domain characteristics were included in this work because they are computationally effective and may be acquired straight from the raw EMG without any processing. This study employed a total of twenty time domain features, which are presented in Table I along with their citations.

TABLE I: Twenty time domain features with abbreviation and references

Feature extracted	Abbr.	References
Average amplitude change	AAC	[6], [7]
Difference absolute standard deviation value	DASDV	[6], [7]
Kurtosis	Kurt	[6], [7]
Log detector	LOG	[6], [7]
Mean absolute value	MAV	[6], [7]
Root mean square	RMS	[6], [7]
Sample entropy	SampEn	[6], [7]
Simple square integral	SSI	[6], [7]
Variance	VAR	[6], [7]
Waveform length	WL	[6], [7]
Skewness	Skew	[6], [7]
Modified mean absolute value type 1	M1AV	[6], [7]
Modified mean absolute value type 2	M2AV	[6], [7]
Wilson amplitude	WAMP	[6], [7]
Zero crossing	ZC	[6], [7]
Slope sign change	SSC	[6], [7]
Integrated absolute value	IAV	[13]
Higuchi fractal dimension	HDF	[13]
Absolute value of temporal moment	AVT	[13]
Mean absolute deviation	MAD	[13]

E. Classification

Due of its robustness and low processing cost, linear discriminant analysis (LDA), the most popular classifier on EMG data, is utilised here [6], [7], [19], [20]. Classification accuracy is computed by averaging the results across nine amputee subjects. Only one feature is taken at a time to check the classification performance and the feature that gives the best classification performance is considered as the best candidate for the PR based MEC.

III. Results

Figure 1 shows the EMG signals obtained from one particular channel for hand near movement at three different force levels, namely medium, high, and low. For the same

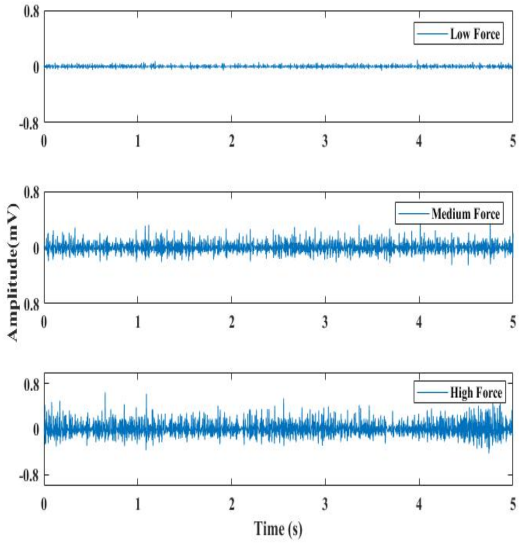


Fig. 1: EMG signal recorded at 3 force levels for hand close movement

movement, it can be seen that the envelope's shape varies for the first three contraction levels.

The EMG properties given in Table 1 have been used to evaluate the effect of force variation on the PR of MEC. The training data is taken from the first two trials of the particular force level, while the test data is derived from the remaining trials from the other two force levels. The is carried out with a 200 ms disjoint window. The reason for choosing this window size is that the segment length contains sufficient information for generating a decision. For real-time operation, a segment length of less than 250 ms is adequate for making a decision. Window size greater than 250 ms will lead to an increase in computational cost and delay for decision. This study examines how each distinct attribute affects the classification accuracy of hand movements. Figure 2 displays the average classification accuracy for the twenty-time domain features provided in Table 1 for nine amputee patients.

A one-way ANOVA was carried out between classification accuracy for the three force levels and the traits. The threshold for significance was fixed at 0.05. The obtained value for p was 0.0008, which is less than 0.05. Comparing the three force levels for 20 features shows that there is a considerable difference in categorization accuracy. RMS and WAMP features are suggested because to their considerably improved classification performance, which can be inferred from the findings. Across all force levels, the SKEW feature appears to be performing least well.

A. Evaluating redundancy of EMG features using histogram plot

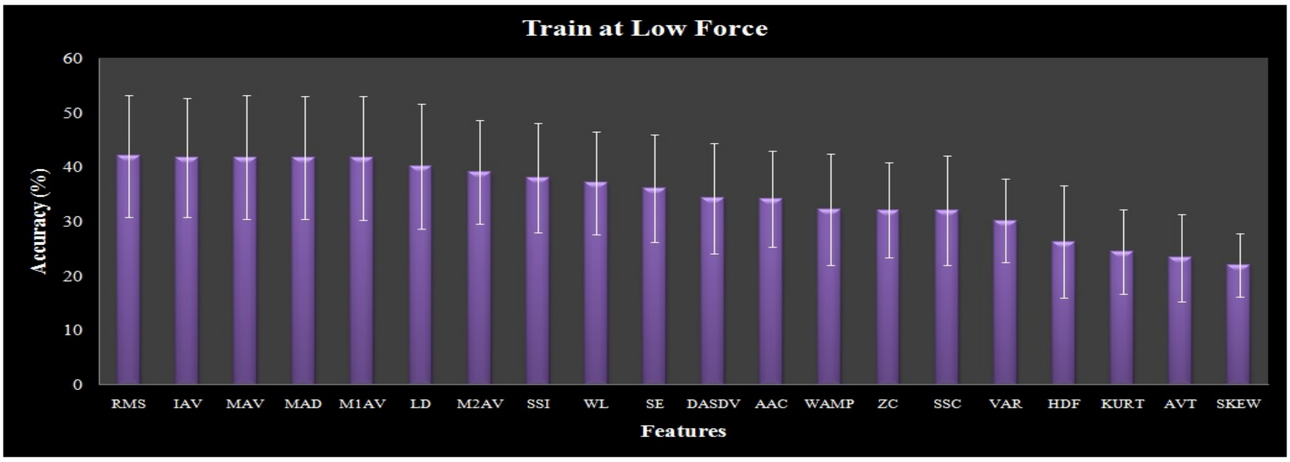
Figure 3 shows the histogram plot of the better performing features such as RMS and WAMP and is compared with the poorer performing SKEW feature.

IV. Discussions

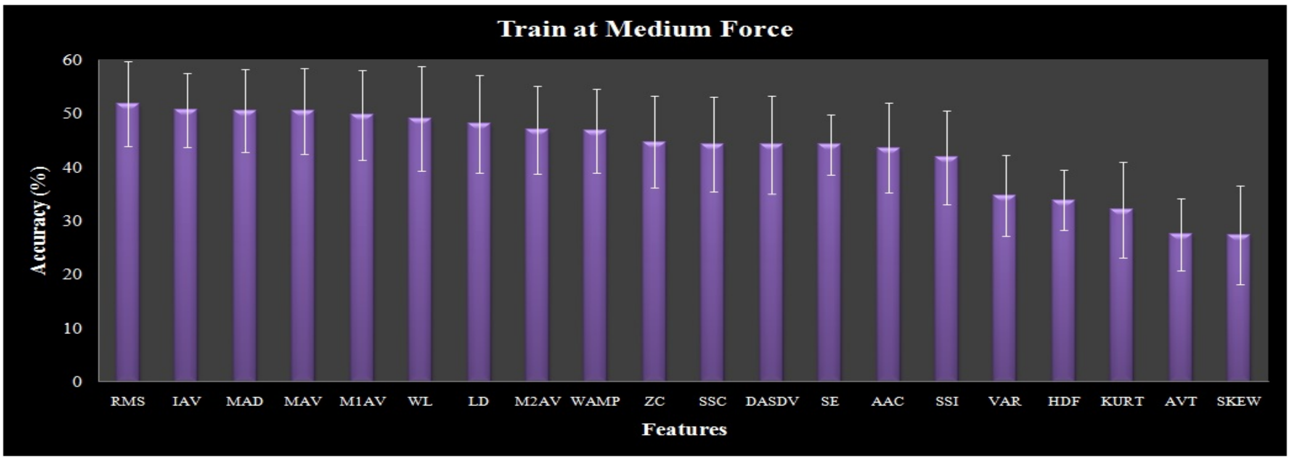
The EMG pattern recognition performance should be invariant against diverse circumstances to allow for practical use of the prosthesis. Finding a reliable set of features to improve the accuracy of EMG pattern categorization was the main goal of this study. Three different force level adjustments were examined for the consistency of EMG features. When force levels vary, PR-based MEC operates less effectively. Amputees find it challenging to train the classifier using data from all force levels, and data analysis takes longer. This study analysed feature performance across three force levels to find a trustworthy feature and enhance the overall classification performance for practical application. It has been found that training with medium power level improves feature performance. The study's benefit is that it may be a means to distinguish between hand movements without training at all force levels. This reduces the amount of time an amputee must spend in training.

From Figure 2, it can be inferred that by using a single feature it is difficult to obtain high accuracy. In the future, multiple EMG feature set could be employed for obtaining high classification accuracy. The dissimilarity in accuracies, as shown in Figure 2 might be due to the difference in relevant information among features.When training data from one force level are paired with testing data from the other two force levels, as shown in Figure 2, the average categorization performance among nine amputee individuals is further examined. The standard deviation is reflected in the error bars. The results demonstrate that the effectiveness of EMG categorization is sensitive to different degrees of force. The classification accuracy is lowest when training is done at a low force level and the classification is confirmed using the data from the other two force levels. When provided at a medium force level, high classification accuracy is seen. It is to be noted that while performing hand motions, amputees have reported difficulty in creating movements with high and low force levels. It is also reported that in some cases, specifically while trying high force levels produced tremor for some subjects [12]. Classification accuracy may be improved further by incorporating data from all force levels for training. All features were affected by the change in force level. The study suggests that RMS feature is a good candidate for training at low and medium force levels whereas WAMP feature is suited for training at high force level. The SKEW feature is observed to be the poorest performing feature for this dataset across all force levels. The EMG patterns collected using RMS and WAMP features may have the strongest repeatability. The low classification accuracy at low and high force levels may be due to the interfering force that alters the EMG patterns. As a result, categorisation accuracy performs worse.

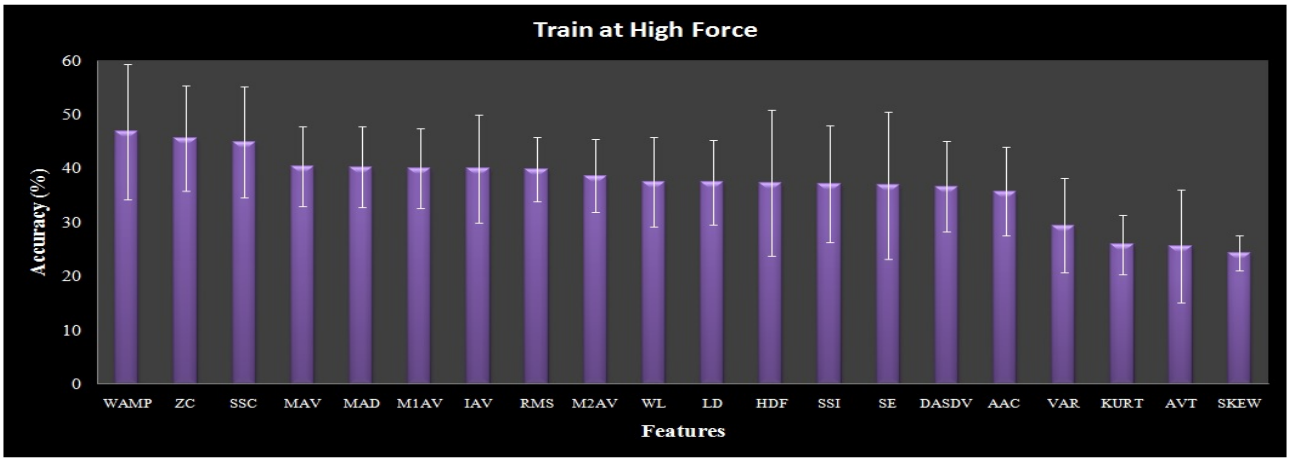
The forearm's gravitational pull from the hand and various muscle fibres' differing force-transmission properties could both contribute to the EMG variation observed [10]. The force level change has a substantial impact on the PR performance when compared to EMG variations brought on by the wrist, hand position, electrode shift, etc. One may think about including training data from all three force levels to get a strong categorization. In comparison to those in the literature, the overall classification accuracy reported in



(a)

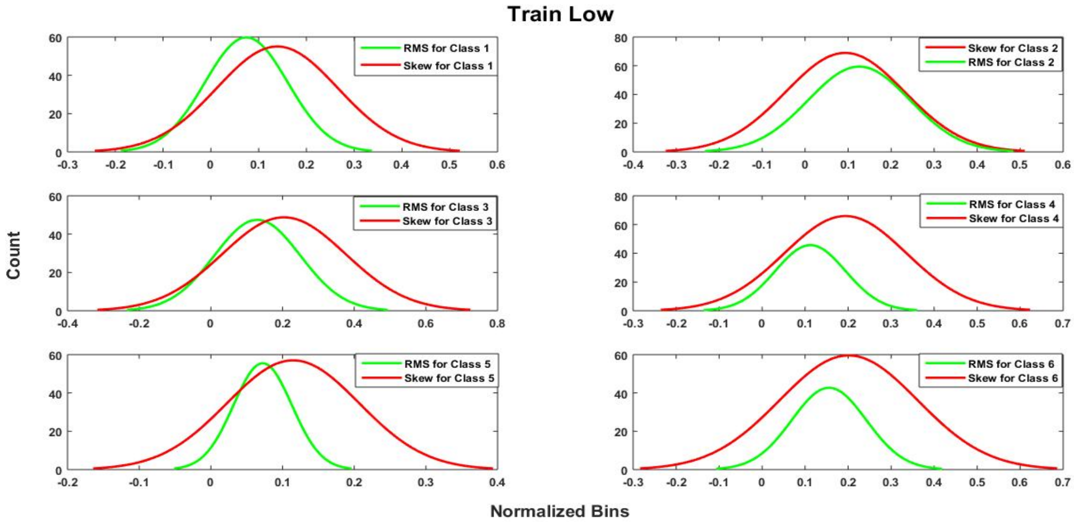


(b)

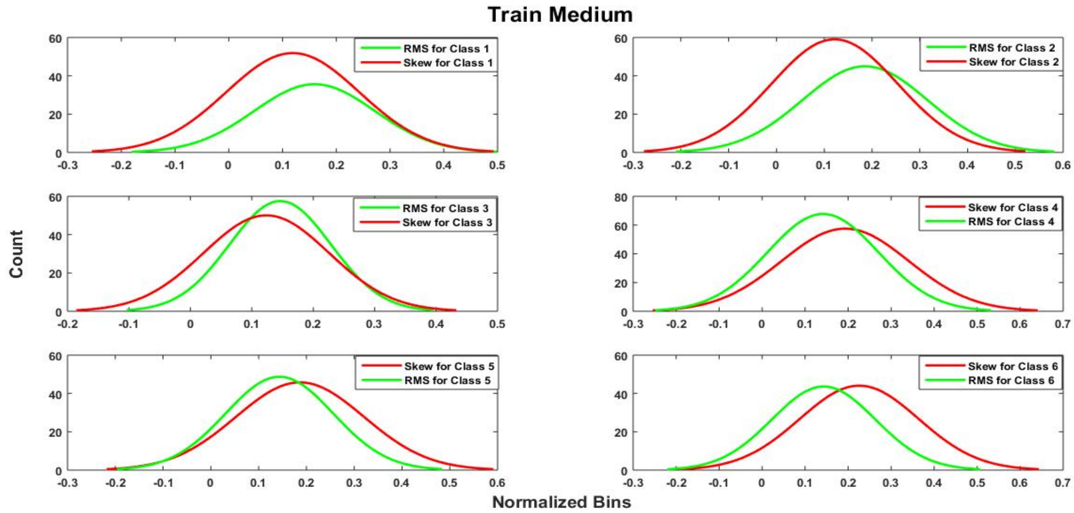


(c)

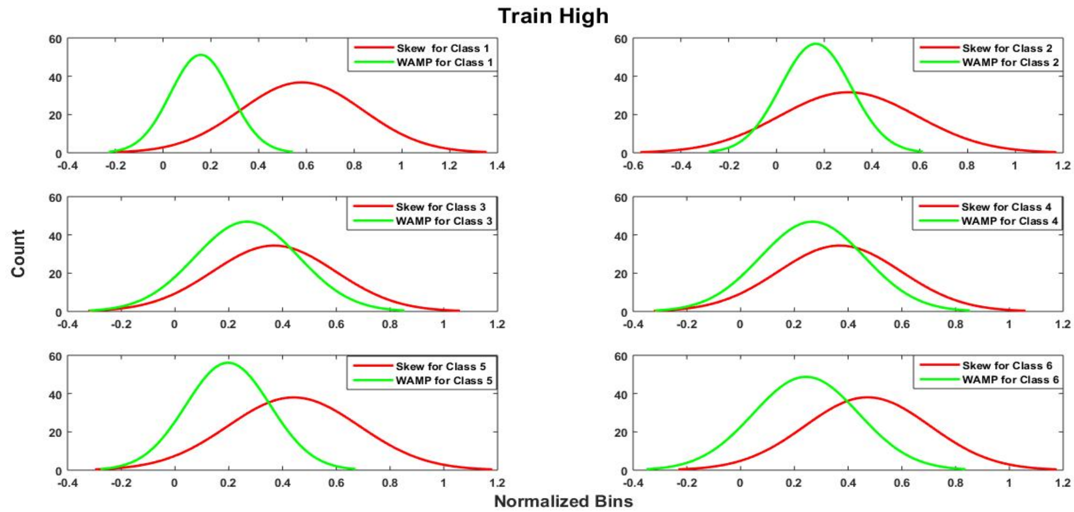
Fig. 2: Average test classification accuracy (%) across ten amputees when training data is from a) low force, b) medium force, and c) high force level for twenty features represented in bar-plot with standard deviation



(a)



(b)



(c)

Fig. 3: Histogram plot for a subject at a) low force level for RMS and SKEW, b) medium force level for RMS and SKEW, and c) high force level for WAMP and SKEW

this research is often lower. This is because it might be difficult to categorise the hand gestures made by amputee patients, especially when varied forces are applied. While training in this study, we only used data from one force level; however, adding training data from additional force levels may enhance classification accuracy. However, adding information from all force levels lengthens the classification process and makes it more difficult, which reduces prosthetic usage and amputee acceptance. Low generalisation capacity is indicated by the low classification accuracy attained in this work, which accurately reflects the actual condition.

The data distribution of histogram plot for RMS and WAMP is narrow, and for SKEW it is wide. This indicates that the distance within the class is less for RMS and WAMP than for SKEW. The results across six classes also show that the mean values of the distribution change for RMS and WAMP feature, whereas it is not changed for SKEW.

This study points out to the fact that many features that perform well for an EMG based PR system might do poorly in the presence of force level variations. It might also be wiser to work further on different training schemes to make the algorithm more robust to these conditions. Finally, it is possible to broaden the analysis to take into account both frequency-domain and time-frequency domain properties. At the cost of increased computing complexity, this might help to get over the inherent constraint of interference susceptibility that the time domain characteristic provides.

V. Conclusion

This study investigates the resistance to changes in force levels of various time domain features used in pattern recognition-based myoelectric control of prostheses. The findings indicate that the accuracy of classifying six categories of hand movements is impacted by modifications in force levels. Therefore, it can be inferred that the impact of changes in force levels must be taken into account when classifying EMG hand movements for transradial amputees. The results indicates that training at all force levels can result in good categorization accuracy. Among the twenty-time domain features, the RMS feature was found to be the least affected when trained at low and medium force levels, while the WAMP feature was the least affected at high force levels. In future studies, real-time classification should be conducted to assess the actual performance of the prosthetic hand.

References

[1] M. Tavakoli, C. Benussi, and J. L. Lourenco, "Single channel surface emg control of advanced prosthetic hands: A simple, low cost and efficient approach," *Expert Systems with Applications*, vol. 79, pp. 322–332, 2017.

[2] P. Geethanjali, "A mechatronics platform to study prosthetic hand control using emg signals," *Australasian physical & engineering sciences in medicine*, vol. 39, no. 3, pp. 765–771, 2016.

[3] 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, no. 3, pp. 419–427, 2011.

[4] M. Jochumsen, A. Waris, and E. N. Kamavuako, "The effect of arm position on classification of hand gestures with intramuscular emg," *Biomedical Signal Processing and Control*, vol. 43, pp. 1–8, 2018.

[5] 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, no. 11, p. 111009, 2016.

[6] A. Phinyomark, F. Quaine, S. Charbonnier, C. Serviere, F. Tarpin-Bernard, and Y. Laurillau, "Emg feature evaluation for improving myoelectric pattern recognition robustness," *Expert Systems with applications*, vol. 40, no. 12, pp. 4832–4840, 2013.

[7] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for emg signal classification," *Expert systems with applications*, vol. 39, no. 8, pp. 7420–7431, 2012.

[8] O. S. Powar and K. Chemmangat, "Dynamic time warping for reducing the effect of force variation on myoelectric control of hand prostheses," *Journal of Electromyography and Kinesiology*, vol. 48, pp. 152–160, 2019.

[9] ——, "Reducing the effect of wrist variation on pattern recognition of myoelectric hand prostheses control through dynamic time warping," *Biomedical Signal Processing and Control*, vol. 55, p. 101626, 2020.

[10] D. Yang, W. Yang, Q. Huang, and H. Liu, "Classification of multiple finger motions during dynamic upper limb movements," *IEEE journal of biomedical and health informatics*, vol. 21, no. 1, pp. 134–141, 2017.

[11] J. He, D. Zhang, X. Sheng, S. Li, and X. Zhu, "Invariant surface emg feature against varying contraction level for myoelectric control based on muscle coordination," *IEEE journal of biomedical and health informatics*, vol. 19, no. 3, pp. 874–882, 2015.

[12] A. H. Al-Timemy, R. N. Khushaba, G. Bugmann, and J. Escudero, "Improving the performance against force variation of emg controlled multifunctional upper-limb prostheses for transradial amputees," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 6, pp. 650–661, 2016.

[13] R. N. Khushaba, M. Takruri, J. V. Miro, and S. Kodagoda, "Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features," *Neural Networks*, vol. 55, pp. 42–58, 2014.

[14] O. W. Samuel, H. Zhou, X. Li, H. Wang, H. Zhang, A. K. Sangaiah, and G. Li, "Pattern recognition of electromyography signals based on novel time domain features for amputees' limb motion classification," *Computers & Electrical Engineering*, vol. 67, pp. 646–655, 2018.

[15] K. Nazarpour, A. H. Al-Timemy, G. Bugmann, and A. Jackson, "A note on the probability distribution function of the surface electromyogram signal," *Brain research bulletin*, vol. 90, pp. 88–91, 2013.

[16] E. P. Doheny, M. M. Lowery, D. P. FitzPatrick, and M. J. O'Malley, "Effect of elbow joint angle on force–emg relationships in human elbow flexor and extensor muscles," *Journal of Electromyography and Kinesiology*, vol. 18, no. 5, pp. 760–770, 2008.

[17] O. S. Powar, K. Chemmangat, and S. Figarado, "A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals," *Biomedical Signal Processing and Control*, vol. 42, pp. 277–286, 2018.

[18] O. S. Powar and K. Chemmangat, "Feature selection for myoelectric pattern recognition using two channel surface electromyography signals," in *Region 10 Conference, TENCON 2017-2017 IEEE*. IEEE, 2017, pp. 1022–1026.

[19] K. Englehart, B. Hudgins, P. A. Parker *et al.*, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 3, pp. 302–311, 2001.

[20] P. Kaufmann, K. Englehart, and M. Platzner, "Fluctuating emg signals: Investigating long-term effects of pattern matching algorithms," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*. IEEE, 2010, pp. 6357–6360.