Borneo Engineering & Advanced Multidisciplinary International Journal (BEAM)
Volume 4, Special Issue (TECHON 2025), September 2025, Pages 10-16

Machine Learning Approach to Multi-Subject EMG Classification of Hand Gestures in Varied Forearm Orientation

Full Paper
Article history
Received
24 June 2025
Received in revised form
10 July 2025
Accepted
19 August 2025
Published online
30 September 2025

Zinvi Fu[1]*

[1]Department of Mechanical Engineering, Politeknik Ibrahim Sultan, KM 10 Jalan Kong Kong, 81700 Pasir Gudang Johor, Malaysia

*Corresponding author: zinvifu@pis.edu.my
Please provide an **official organisation email** of the corresponding author

Abstract

The electromyogram (EMG) is a bio signal which manifests in conjunction with muscle contraction. It can be used for neuro-muscular diagnosis, ergonomic analysis and machine control including prosthetics and teleoperation. Although in recent years there has been advances in detection and gesture prediction methods including artificial intelligence, machine learning still plays a fundamental role as the EMG is a waveform-based signal. As a biological signal, the EMG signal can vary throughout the day depending on the placement of the electrodes, muscle contraction level and fatigue of the individual. Moreover, due to the variability between individuals, a prediction model trained on an individual may not provide accurate prediction for another individual. Therefore, there is a strong motivation to study the variation of the EMG waveform and identify the most universally classifiable gestures. The main objective of this work is to measure variability of the forearm EMG signals between individuals and to classify the gestures based on training data from various forearm positions. In this work, the EMG signals of nine gestures of the hand was performed with the forearm in neutral, pronation and supination. The variability analysis was performed with normalized cross-correlation (NCC), then training models were developed with various time and frequency domain features and classifiers. Five-fold cross-validation was used to validate the classification accuracy. The main classification results show that the best classification accuracy can be achieved with the use of 10-Hz linear envelope and linear dependent analysis (LDA) classifier which yielded 89-92% accuracy for the forearm flex and extend motion. The NCC of these opposing gestures, also yielded a coefficient of 0.78 which shows a significant difference in the gestures.

Keywords: - Electromyography, machine learning, artificial intelligence, machine control

1. Introduction

The electromyogram (EMG) is a biological electric signal that manifests around the muscle when a contraction is performed. Muscle contraction continues if the EMG exists around the muscle. EMG-based techniques are capable of accurately distinguishing natural human motion such as subtle finger movements and wrist motions by directly sensing and decoding muscular activity (Inam et al., 2021). In recent years, artificial intelligence is used to identify or predict EMG signals. The steps involve data collection, preprocessing, feature extraction, model development, model training and classification (Jonge et al., 2024).

In manufacturing and process engineering, EMG signals can be used in monitoring processes to identify activity, conditions, and capacities of workers in real-time EMG signals can be used in monitoring processes to identify activity, conditions, and capacities of workers in real-time (Olmo & Domingo, 2020a). For this common task, the gestures must be natural and easy to remember, comfortable and non-fatiguing, and provide the precision necessary to minimize error (Lin et al., 2019).

Production machines or workstations are not bounded to a single user and is usually operated by several different operators. In comparison, medical or domestic applications (usually robotic prosthetics) are tailor-made to specific users and their residual limbs. For this reason, reducing the training time due to multi-users is crucial.

The EMG signal as a input signal is prone to variations due to hand orientation, muscle activation levels and fatigue. Therefore, gestures must be selected based on a consistent EMG production. The objective of this work is to determine the variability of the EMG signal across multiple subjects and classify the EMG signals of selected forearm gestures in various positions.

2. Literature Review

Production machines or workstations are not bound to a single user and are usually operated by several different operators. In comparison, medical or domestic applications (usually robotic prosthetics) are tailor-made to specific users and their residual limbs. For this reason, reducing the training time due to multi-users is crucial.

To the best of knowledge, there is no recommendation on the number of individuals operating a production machine. Instead, it is determined by the production volume and complexity of the task, and availability of trained operators. EMG devices such as HMI collaboration systems and exoskeletons are specialized equipment in the workplace. While there is no data on the norms of the number of operators per device, simulated studies have been performed on samples of between three to seven operators. On the other hand, EMG studies on fatigue, risk and injury monitoring ranged from five to 46 individuals (Olmo & Domingo, 2020b).

The EMG signal of a gesture produced by an individual is influenced by muscle recruitment during the gesture, and inter-subject variations exist in the EMG produced by a group of people. Many factors contribute to its variability. These factors can be linked to the person's physiological state (gender, age, presence of pain, fatigue or discomfort, or prevention of their onset), to their expertise and to the characteristics of the task to be performed (Gaudez et al., 2016). Furthermore, variability in the pace, range of motion and arm position during repetitive tasks over long periods can differ by 15% (Srinivasan et al., 2015). It is difficult to perform the same task in the exact same manner twice. A simple task of moving an object into a target area by hand required 25 times of training to reduce the variability by 75% (Lametti et al., 2007).

The variations in motion are directly related to the muscle recruitment, and the EMG produced will also reflect the variability of the gestures across a group of different operators. Therefore, the usability of the EMG system will require robustness towards the variability due to users, hand position and hand side (Khushaba et al. 2016).

3. Methodology

The focus of the work here is the application of variability analysis and cross-validation in addition to classification. Fig. 1 shows the graphical methodology of the work done.

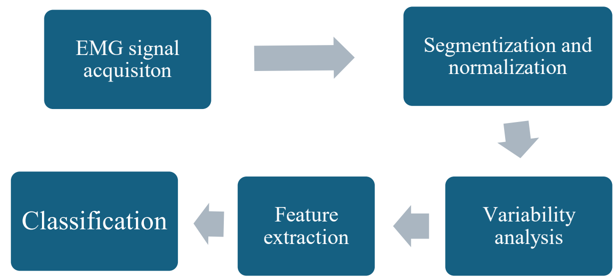


Fig. 1: Graphical methodology of the experiment

3.1 Experimental Setup

For the experiment, EMG data was acquired from twenty subjects. Electrodes were placed radially round the lower forearm and the subjects performed six gestures as detailed in Fig. 2. 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 gap of equal length. Each sequence lasted between 30-40 s. Details of the procedure and setup can be found in (Fu et al., 2021). The collected signal database was re-evaluated with methods detailed in this work. The work here is performed with variability analysis and the signals were acquired with a custom-built differential amplifier with a common-mode rejection ratio of 93.36 dB while digitization was performed with the Texas Instruments NI-cDAQ 9178 digital acquisition unit. Further details of the design and analysis of the bio signal amplifier used here can be found in Fu et al. (2023).

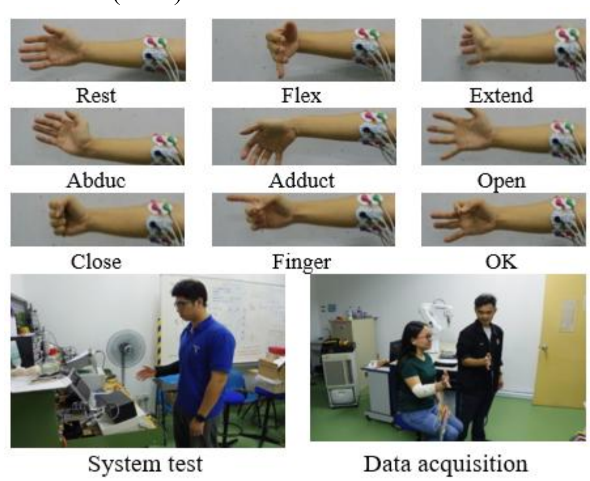


Fig. 2: Selected gestures and general experimental setup

3.2 Feature Extraction

The selected features for the study are detailed in Table 1. The commonly used features consisting of nine time-domain and three frequency domain types were chosen for their simple applications.

Table 1: Total of vehicles for each entrance

Time-Domain Features
Moving average (MAV), $MAV = \frac{1}{N}\sum_{n-1}^{N}\lvert x_n \rvert$
Root mean square (RMS) $RMS = \sqrt{\frac{1}{N}\sum_{n-1}^{N} x_n^2}$
Waveform length (WLT), $WLT = \sum_{n=1}^{N-1} x_{n+1} - x_i$
Integrated average (IAV) $IAV = \sum_{N=1}^{N}\lvert x_n \rvert$
Autoregressive (AR) $AR = \sum_{1}^{M} a_i x(n-i) + e(n), n = 0..N-1$ $M = model\ order$ $a_i = AR\ coefficients$
Slope sign change (SSC) $SSC = \frac{1}{N}\sum_{n=2}^{N-1} f[(x_n - x_{n-1}) \times (x_n - x_{n+1})]$ $f(x) = \begin{cases} 1, & x \geq threshold \\ 0, & otherwise \end{cases}$
Linear envelope, $LE = Z_{Butterworth}(\lvert x(n) \rvert), f_c = 10\ Hz$
Frequency-Domain Features
Mean frequency (MNF) $MNF = \frac{\sum_{n=1}^{N} f_n P_n}{\sum_{n=1}^{N} P_n}$
Median frequency (MDF) $MDF = \frac{1}{2}\sum_{n=1}^{N} P_n$
Peak frequency (PKF) $PKF = f(P_{max})$
Sampling frequency = 5000Hz Window length = length of sample ≈ 2000 Number of windows = 1 Overlap = none

3.3 Variability Analysis

The repeatability of the data was assessed with and cross-correlation (Park et al., 2012 & Rodrigues et al., 2017). The cross-correlation method is well-suited for measuring variation tendency between waveforms patterns across with value that can be interpreted in the form of a coefficient. Values ranging from 0.00 to 0.25 indicate no or only slight similarity between waveforms; values from 0.25 to 0.50 suggest a fair degree of similarity; values from 0.50 to 0.75 indicate moderate similarity, and values above 0.75 correspond to highly similar. The mean normalized cross-correlation coefficient (NCC) per gesture is defined by equation (1).

$$\sum_{j=1}^{j=20}\frac{1}{20}\left[\frac{\sum_{i=1}^{6} a_{ij}.b_{ij}}{\sqrt{\sum_{i=1}^{6}\left(a_{ij}^2\right).\sum_{i=1}^{6}\left(b_{ij}^2\right)}}\right] \tag{1}$$

Where a and b denote the two gestures to be compared against, and i and j are the feature and subjects, respectively. In other words, the cross-correlation per gesture is calculated by the six-channel features i of subject j against the features of every other subject. Each complete iteration then produces the NCC of the subject j against the remaining 19 subjects. Thereafter, the mean NCC was calculated over the cross-correlation of the 19 iterations. Since self-correlation of the same subject will result in a coefficient of 1.0, this result is not taken into calculation of the mean NCC to avoid skewing the mean towards a false high correlation.

3.4 Classification

For classification, the LDA, KNN and SVM classifiers were chosen because these classifiers are computationally efficient without sacrificing performance (Basak et al., 2021). The LDA was used, because of its reliability and low computational cost (Geng et al., 2012). Table 2 shows the classifiers and their parameters.

In the 5-fold cross-validated classification, the training and test data were pooled together and divided into five equal parts. The single feature extracted produced six feature values per gesture. The 11 elements of features extracted were concatenated horizontally to form a 66 (6×11 features) dimension feature vector. The rows consist of the gestures per trial, which consists of 9 gestures per trial.

Table 2: Selected classifiers and their parameters

	KNN	DA	SVM
Classifier model tuning parameters	Number of neighbours: 4 Distance: Euclidean	Type: Linear	Kernal: Gaussian Kernal scale: 1.64 Box constraint: 5
Validation	5-fold cross validation		

For intra-subject classification, the classifier model was trained with 5 sets of training data, each set consisting of 9 individual gestures. while one remaining of data was reserved for testing purposes, as shown in Table 3. For instance, the subject-specific classifier model for the neutral position for both left and right hands $DN_{\{R,L\}}$ position was trained with 5 $DN_{\{R,L\}}$ datasets consisting of 5 trials. Since there were 5 trials, a total of 45 (5 × 9) gestures were obtained and arranged in rows according to gestures.

In supervised learning, the feature vectors were concatenated in rows of gestures then by trials, where each row of feature vector was assigned a gesture class. The test data consists of the same data as the training set, however 5-fold cross validation applied to ensure ideal data fitting. For the position-independent test, $DN_{\{R,L\}}$ was used as the training data while $DP_{\{R,L\}}$ and $DS_{\{R,L\}}$were the test data. For the hand-exchange classification, the left-hand data in DN, DP and DS, of the $LH_{\{DN, DP, DS\}}$ was the training data while the right-hand data $RH_{\{DN, DP, DS\}}$ and vice versa.

Statistical analysis was performed with one-way repeated-measure analysis of variance (rmANOVA) to determine the significance of the results in terms of the effect of multi-users, hand rotation, hand-exchange and to evaluate the performance of the feature-classifier choice. Bonferroni correction was used to evaluate the pairwise classification accuracy between each classifier-feature combination. All statistical analysis was performed with Matlab.

Table 3: Training and test data for intra-subject classification

Condition	Number of training data sets, (size)		Number of test data set, (size)	
Reference (same hand, same position)	$DN_{\{R,L\}}$ $DP_{\{R,L\}}$ $DS_{\{R,L\}}$	5 (1 subject × 5 trials × 9 gestures =45)	$DN_{\{R,L\}}$ $DP_{\{R,L\}}$ $DS_{\{R,L\}}$	1 (1 subject × 1 trials × 9 gestures =9)
Inter-position (same hand, varied position)	$DN_{\{R,L\}}$	5 (1 subject × 5 trials × 9 gestures =45)	$DP_{\{R,L\}}$, $DS_{\{R,L\}}$	5 (1 subject × 5 trials × 9 gestures =45)
Between-hand ((a) different hand, same position, (b) different hand, varied position)	$LH_{\{DN,DP,DS\}}$ $RH_{\{DN,DP,DS\}}$	5 (1 subject × 5 trials × 9 gestures =45)	$RH_{\{DN,DP,DS\}}$ $LH_{\{DN,DP,DS\}}$	5 (1 subject × 5 trials × 9 gestures =45)

Cross-validation: 5 fold

4. Result and Discussion

4.1 Variability Analysis

The results of the inter-gesture mean NCC is presented in Table 4. The mean NCC obtained for most gestures are above 0.90 for all gestures, except for the OPN and CLS gestures which ranged from 0.90 to 0.95. This is interpreted as a low similarity in the inter-subject features of these gestures and indicates a lower classification result compared to other gestures. Hence it is necessary to perform the classification with various features and classifiers, as some features are less sensitive to inter-subject variations. Not tabulated in the results are the NCC on two different gestures.

The NCC of two opposing gestures, FLX and EXT features, yielded a coefficient of 0.78. This shows that the features of these two gestures are completely different in terms of pattern. Therefore, the reported NCC is interpreted with the following guidelines: 0.97 to 1.00 – nearly identical to identical, 0.9 to 0.96 – highly similar, 0.85 to 0.89 – similar, below 0.85 – different signal.

Table 4: Inter-gesture mean 20-subject mean NCC

	DN_L	DP_L	DS_L	DN_R	DP_R	DS_R
DN_L	0.99					
DP_L	0.95	0.99				
DS_L	0.93	0.91	0.99			
DN_R	0.89	0.89	0.88	0.99		
DP_R	0.86	0.88	0.87	0.92	0.99	
DS_R	0.87	0.86	0.86	0.94	0.95	0.99

Inter-subject rmANOVA significance ($p \approx 1.0$), except for OPN ($p \approx 0.94$), CLS ($p \approx 0.94$)

RmANOVA showed a high p-value of almost 1.00 showing the statistical difference between the feature extracted from all subjects is insignificant. In other words, there is a low degree of variation in the features of a gesture among the subjects. Since ANOVA measures the variation of data in terms of means and SD rather than pattern, the reported p-value does not fully describe the inter-gesture variation. Since the features were normalized, all gestures had an amplitude range of between 0.00 to 1.00 with a similar mean and median. However, the high value serves to ensure that the variation in terms of amplitude is minimal.

In the inter-position, between-hand mean NCC calculation shown in Table 5. The mean NCC per gesture was calculated in a similar manner but with the signals from the two compared conditions (position and hand). The mean NCC was obtained by averaging the means of the NCC of all nine gestures. The inter-position, between hand rmANOVA reported a high p-value indicating that there is little variation in the amplitude of the features. To test the significance of the between-condition NCC, the conditions were arranged into the following categories: i) same-hand, same position ii) same position-different hand, iii) different-hand, iv) different position. Bonferroni post-hoc test reported that the mean NCC of the four categories in order are i) 0.99 ($p=0.01$), ii) 0.92 ($p=0.01$) iii) 0.89 ($p=0.01$) and iv) 0.88 ($p=0.01$) respectively. The results revealed that the features are similar in the same position-hand and varied during rotation and the data of the left and right hand are generally not interchangeable. However, there may be feature-classifier combinations that are robust to these variations.

Table 5: Inter-position and between-hand mean NCC

	DN_L	DP_L	DS_L	DN_R	DP_R	DS_R
FLX	0.98	0.98	0.97	0.98	0.98	0.98
EXT	0.99	0.99	0.99	0.99	0.99	0.99
ABD	0.98	0.98	0.97	0.97	0.96	0.96
ADD	0.95	0.98	0.98	0.97	0.99	0.99
OPN	0.93	0.91	0.92	0.93	0.91	0.92
CLS	0.93	0.92	0.91	0.93	0.91	0.90
FIN	0.96	0.95	0.95	0.98	0.96	0.94
OKE	0.97	0.95	0.96	0.98	0.97	0.96
TMB	0.96	0.96	0.95	0.96	0.95	0.94

Inter-subject rmANOVA significance ($p \approx 1.0$), except for OPN ($p \approx 0.94$), CLS ($p \approx 0.94$)

4.2 Intra-Subject Classification Results

The intra-subject classification was performed to assess the classification accuracy on a single subject, which serves as a reference. Table 6 shows the overall classification accuracy of all the gestures in all conditions. The training data and test data is outlined in the rows and columns, respectively. For example, gestures classified with training data DN_L and test data DN_L can be found in row 1, column 1 (90.3%), while the results for training data DP_R and test data DN_R is situated at row 5, column 4 (84.7%). The classification accuracy reported was calculated as the percentage of gestures classified correctly over the 20 subjects for every 9 gestures.

The reference group, marked by the diagonal line, consists of classification of gestures trained and tested in the same hand and position. The mean classification of the reference group is 91.73%, which is the highest among the three groups. The second group, inter-position consists of gestures classified in the same hand in different positions with the training and test data rotated around the DN, DP and DS positions had a mean of 85%. The third group, between-hand, yielded the lowest mean classification accuracy of 68%. RmANOVA reported that the difference between the classification accuracy between the three groups are significant, $p<0.01$ in all conditions. The standard deviation and p value indicate the variation of the classification accuracy of the classification groups. The reference group gestures are not affected by the hand rotation. Therefore, its classification result is the highest, with a lower variation as indicated by the lower standard deviation (6.45) and p value (0.65). An increase in the standard deviation and p value of the inter-position and between-hand groups shows a significant increase in variation in the classification results among the subjects and gestures.

Table 6: Mean inter-position and between-hand classification results, calculated over 20 subjects, all feature-classifier combinations

	Testing data					
Training data	DN_L	DP_L	DS_L	DN_R	DP_R	DS_R
DN_L	94.3	83.6	85.4	67.3	64.5	65.2
DP_L	87.4	90.1	83.2	63.4	71.4	68.2
DS_L	85.6	84.6	89.1	64.2	65.3	82.5
DN_R	80.9	67.8	69.2	93.2	86.4	83.6
DP_R	73.1	72.8	68.3	84.7	91.5	85.6
DS_R	69.0	67.0	67.4	86.6	88.7	92.2

Within-group standard deviation and rmANOVA p-value
Reference: 6.45 (p=0.63)
Inter-position: 8.36 (p=0.56)
Between-hand: 11.32 (p=0.47)

With reference to Fig. 2, the overall classification accuracy by gestures for the intra-subject condition was high, except for the between-hand condition. In the reference condition, all gestures were able to be classified with high accuracy of 92% mean, regardless of feature or classifier. Even with a small trial sample (n=5), the EMG signals are produced by one person and, therefore, consistent across the trials. Comparing the features in Fig. 3, all features were able to produce high classification results of over 90% regardless of gestures and classifiers. However, due to variability introduced by the inter-position and between-hand conditions, the mean classification dropped to 87% and 70% respectively. The classifier-wise comparison results shown in Fig. 4 show LDA has the highest performance (85%) compared to KNN (mean 81%) and MVSM (mean 70%). However, the MVSM had the smallest drop in classification accuracy across the three conditions.

For intra-subject classification, the high classification results are largely attributed to the similar EMG signals produced by one person. Since the electrode placement and physiological factors are constant, the discrepancies that caused misclassification were due to contraction force. When further variabilities were introduced in the inter-position classification, the classification accuracy was lower due to muscle activity from the pronator muscles. Although the finger is controlled by deep muscles which rotate with the wrist, the finger gestures did not experience a reduction in classification accuracy. This was because in an untargeted electrode configuration, the EMG signals were taken collectively, and gestures performed in rotation were recorded independently of the gestures in neutral position.

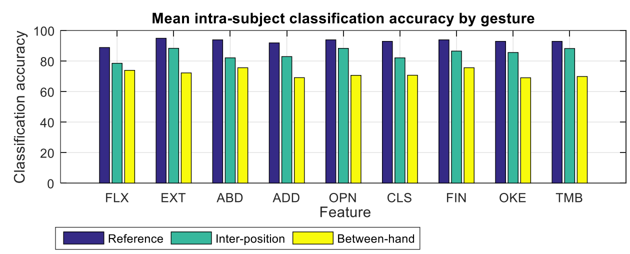


Fig. 2: Intra-subject classification results by gestures, averaged across all features (mean SD: 8.59)

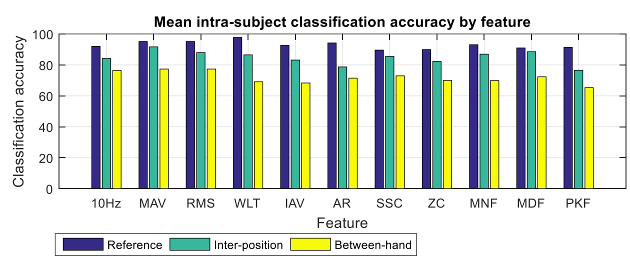


Fig. 3: Feature-wise classification accuracy, averaged across all gestures (mean SD: 10.25)

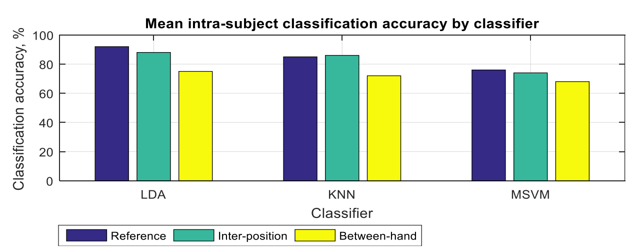


Fig. 4: Intra-subject classification results by gestures, averaged across

4.3 Best Achievable Classification Accuracy

The combination of 10 Hz linear envelope feature and LDA classifier was consistent in providing the highest achievable classification results. The LDA had the advantage of a lower computation cost. In comparison, the KNN classifier requires the configuration of the k value, which must be optimized through cross-validation. In this study, the MVSM classifier was slow and did not provide good classification results.

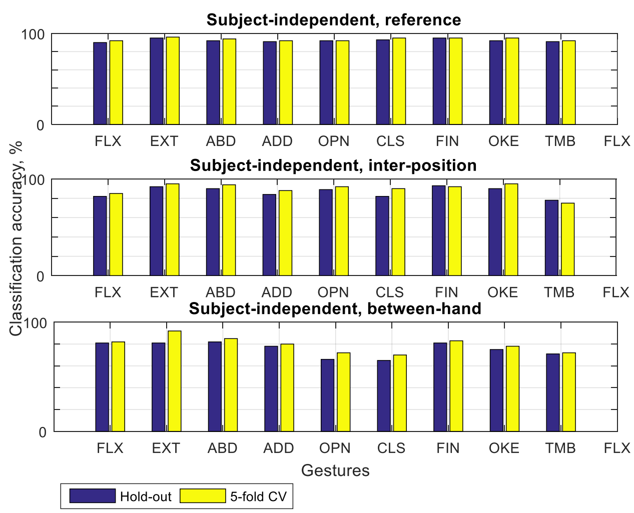
With the 10 Hz – LDA combination, it is possible to achieve up to 90% for the FLX, EXT, ABD, ADD gestures in all conditions (reference, inter-position and between-hand). On the other hand, the frequency-domain features MNF and MDF could also provide high classification results, however with a margin error which is larger. Thus, the error margin is an important factor to consider because it will increase as the number of gestures or degree of freedoms increase. The best classification results for the intra-subject condition with 10 Hz – LDA is shown in Table 7

Table 7: Best achievable classification accuracy with 10Hz – LDA

	FLX	EXT	ABD	ADD	OPN	CLS	FIN	OKE	TMB	Mean
Reference	89	92	90	81	70	64	78	88	80	80
Inter-position	82	91	91	82	63	53	65	84	75	76
Between-hand	80	80	83	63	42	51	47	53	46	63

4.4 Cross Validation Results

Fig. 5 shows the comparison of both validation methods for the intra-subject classification. In all conditions, the CV method had marginally higher classification results, however, there was little difference in the classification accuracy of both methods (mean difference = 3%). This shows that the training and test data in both validation methods had highly similar features, which was expected as the EMG data from one subject is highly consistent.



Mean classification accuracy

Reference	Inter-position	Between-hand
Hold-out: 92%	Hold-out: 84%	Hold-out: 73%
5 fold CV: 95%	5 fold CV: 91%	Hold-out: 79%

Fig. 5: Comparison of hold-out validation and 5-fold cross-validation for the intra-subject classification

5. Conclusion and Recommendations

In this work, the variability of the EMG was obtained with the normalized cross-correlation (NCC) was used to normalize the signal. The gestures OPN and CLS were found to have higher variability due to the contracting force, which subsequently affected the overall classification results.

The intra-subject classification served as a reference to mark the maximum possible classification results. In the intra-subject classification, the classification results were high for gestures in the reference and inter-position conditions. However, the classification accuracy dropped with hand-exchange. The variability of the OPN and CLS gestures did not affect the overall classification results as they were consistent across a single subject.

In this work, the classifier model is trained in individual subjects. For future work, the scope of the work can be expanded to perform classification on a subject with a model trained on another subject.

Author Contributions: The research study was carried out successfully with contributions from all authors.

Conflicts of Interest: The authors declare no conflict of interest.

References

Basak, H., Roy, A., Lahiri, J. B., Bose, S., & Patra, S. (2021). SVM and ANN based Classification of EMG signals by using PCA and LDA. *arXiv preprint arXiv:2110.15279*.

Fu, Z., Hashim, A. Y. B., Jamaludin, Z., & Mohamad, I. S. (2021). The Classification of EMG Signals with Zero Retraining in the Influence of User and Rotation Independence. *International Journal of Integrated Engineering*, *13*(1), 120-129.

Fu, Z., Hashim, A. Y. B., Jamaludin, Z., & Mohamad, I. S. (2023). Design and Development of A Low-Cost Electromyogram Amplifier for General-Purpose Biosignal Amplification. *Jurnal Sains Sosial dan Pendidikan Teknikal| Journal of Social Sciences and Technical Education (JoSSTEd)*, *4*(1), 113-126.

Gaudez, C., Gilles, M. A., & Savin, J. (2016). Intrinsic movement variability at work. How long is the path from motor control to design engineering?. *Applied ergonomics*, *53*, 71-78.

Geng, Y., Zhou, P., & Li, G. (2012). Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees. *Journal of neuroengineering and rehabilitation*, *9*(1), 74.

Inam, S., Al Harmain, S., Shafique, S., Afzal, M., Rabail, A., Amin, F., & Waqar, M. (2021, April). A brief review of strategies used for EMG signal classification. In *2021 international conference on artificial intelligence (ICAI)* (pp. 140-145). IEEE.

Jonge, S. D., Potters, W. V., & Verhamme, C. (2024). Artificial intelligence for automatic classification of needle EMG signals: A scoping review. *Clinical Neurophysiology*, *159*, 41-55.

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.

Lametti, D. R., Houle, G., & Ostry, D. J. (2007). Control of movement variability and the regulation of limb impedance. *Journal of neurophysiology*, *98*(6), 3516-3524.

Lin, J., Harris-Adamson, C., & Rempel, D. (2019). The design of hand gestures for selecting virtual objects. *International Journal of Human–Computer Interaction*, *35*(18), 1729-1735.

Olmo, M. D., & Domingo, R. (2020a). EMG characterization and processing in production engineering. *Materials*, *13*(24), 5815.

Olmo, M. D., & Domingo, R. (2020b). EMG characterization and processing in production engineering. *Materials*, *13*(24), 5815

Park, K., Dankowicz, H., & Hsiao-Wecksler, E. T. (2012). Characterization of spatiotemporally complex gait patterns using cross-correlation signatures. *Gait & Posture*, *36*(1), 120-126.

Rodrigues, C., Correia, M., Abrantes, J. M., Nadal, J., & Rodrigues, M. A. B. (2017, July). Consistency of surface electromyography assessment at lower limb selected muscles during vertical countermovement. In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 402-405). IEEE.

Srinivasan, D., Samani, A., Mathiassen, S. E., & Madeleine, P. (2015). The size and structure of arm movement variability decreased with work pace in a standardised repetitive precision task. *Ergonomics*, *58*(1), 128-139.

