Analysis of High-Density Surface Electromyogram (HD-sEMG) signal for thumb posture classification from extrinsic forearm muscles

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Abstract: For amputees, the development of cybernetic hands that closely resembles the functions of real hands is essential for comfortability and functionality purposes. Controlled by intrinsic and extrinsic muscles, human thumb plays a major role in differentiating hand gestures. For those who have lost their intrinsic hand muscles, any information about muscle activities that can be obtained from the extrinsic muscles will be essential to control the thumb. Focusing on transradial amputees, this research investigates the relationship between extrinsic muscles to characterize the actual thumb posture. A High-Density Surface Electromyogram (known as HD-sEMG) recording device and a portable thumb force measurement system were used to collect forearm Electromyogram (EMG) signals from a total of 17 subjects. For the flexion motion, the subjects were asked to repetitively place their thumbs at rest before exerting 30% of their individual Maximum Voluntary Contraction (MVC) on a load cell by following a designated trajectory presented on a designated Graphical User Interface (GUI). The trajectory was set to four different postures, namely, zero-degree, thirty-degree, sixty-degree, and ninety-degrees. Feature extraction was then performed by extracting the Absolute Rectified Value (ARV) and Root Mean Square (RMS) values of the forearm HD-sEMG signals before being classified using Lazy.IBK. The results revealed that the ARV features, which were extracted from HD-sEMG from both posterior and anterior hand sides successfully achieved the highest correctly classified percentage of 99.48%. The findings of this study are significant for the development of a dedicated model-based control framework for prosthetic hand’s development to be used by transradial amputees in the future.

Subjects: Dynamics & Kinematics; Biomechanics; Biosensors

PUBLIC INTEREST STATEMENT

The human thumb contributes to more than 50% of the hand’s functions and gestures. Losing the thumb due to amputation can cause an individual to face difficulties in performing routine daily activities. Cybernetic hands can assist these individuals and are essential to have comfortability and good functionality. Focusing on extrinsic (inner) forearm muscles, this study investigates the relationship between the dedicated muscles and the actual thumb posture. 17 participants of the study were asked to repetitively place their thumb on a dedicated platform at four different angles denoted as zero-degree, thirty-degrees, sixty-degrees, and ninety-degrees, respectively in both relax and stress conditions. Their High-Density Surface Electromyogram (HD-sEMG) signals were recorded. After extracting the collected data from both the forearm anterior and posterior, the results showed that 99.48% of the HD-SEMG signals were successfully classified using the Lazy.IBK algorithm. The findings of this study are important in the development of prosthetic hands for the resemblance of normal thumb functionality.
Keywords: thumb posture; high density surface electromyogram (HD-smg); forearm anterior and posterior; maximum voluntary contraction (MVC)

1. INTRODUCTION

Human hand is an important body part that is normally used for controlling and handling daily activities such as grasping, pinching, and gripping (Yan et al., 2019). Since the thumb is the only opposable digit to the other four fingers, it plays a particularly critical role in gripping. Thumb is also essentially indispensable as it contributes to at least 50% of the majority of hand functions and gestures (Il Park et al., 2012). Statistics reveal that there were approximately 1.6 million individuals who live with limb loss in the United States and it is also estimated that the number will double by 2050 (Ziegler-graham et al., 2008). Therefore, the development of prosthetic hands that closely resemble the function of real hands is essential for comfortability and functionality purposes.

Figure 1 shows the two categories of amputees, namely transradial and transcarpal amputees. Transradial amputations occur in the forearm area, and the amputations are typically performed at a ratio of 1:1 of the forearm length, resulting in total loss of the interconnection between the intrinsic and extrinsic muscles (Dupan et al., 2018; Maduri & Akhondi, 2020). Meanwhile, transcarpal amputation involves the loss of the palm only while preserving some intrinsic muscles and all extrinsic muscles. Both transcarpal and transradial amputations can be caused by traumatic injury due to accidents. In general, flexion and extension motions of the wrist are still preserved, as more hand muscle activity data can be extracted from transcarpal amputees than transradial amputees (Maduri & Akhondi, 2020).

Intrinsic muscles are located within the hand palm itself, whereas extrinsic muscles are located in the forearm. On one hand, intrinsic muscles play a vital role in controlling both the thumb posture and also the strength of the force being exerted by thumb (Adewuyi et al., 2016). As shown in Figure 2, there are five intrinsic muscles, namely, Abductor Pollicis, Abductor Pollicis Brevis, Flexor Pollicis Brevis, and Opponens Pollicis. Even though the intrinsic muscles are the main muscles that control the thumb, the synergistic combination between the intrinsic and extrinsic muscles plays an important role in both hand gesture and force exertion.

On the other hand, extrinsic muscles consist of various muscles that perform different functions, for example, the Flexor Pollicis Longus controls the thumb digit from the anterior side (Flexor
Pollicis Longus, 2021). As for the posterior side, there are three muscles, namely, the Abductor Pollicis Longus, which controls the abduction and extension of the thumb (Physiopedia contributors, 2021), Extensor Pollicis Brevis, which is a mild abductor of the thumb (Jabir et al., 2013), and Extensor Pollicis Longus, which extends the interphalangeal joint of the thumb (Physiopedia contributors, 2021) as illustrated in Figure 3. For the transradial amputees, due to the loss of the intrinsic hand muscles, one of the options to extract the information in classifying the thumb posture is through their extrinsic muscles.

Throughout the last decade, researches have achieved significant progress in the field of prosthetic hand development that utilizes Electromyogram (EMG) measurements (Sánchez-Velasco et al., 2019). For instance, previous research has demonstrated the feasibility of using EMG signals to control robotic hand prostheses (Khushaba et al., 2017; Mastinu et al., 2019; Wijk
EMG is a biosignal that represents electrical potentials generated by a particular muscle during gestures, movements, and force exertion. These electrical activities are generated by an accumulation of motor neurons which excite the muscle fibres (Phinyomark et al., 2012; Phinyomark et al., 2013). There are two types of EMG, namely invasive and non-invasive. Based on the latest trend, non-invasive Surface Electromyography (sEMG) is more commonly used both in prosthesis development (Chowdhury et al., 2013) and also in clinical applications such as physiology (Enoka, 2019) since this technique is comfortable, painless, and also extensive methods have been previously developed for processing and analyzing the EMG signals (Cronin et al., 2015).

Continuous research and development have revealed several limitations in the analysis of conventional sEMG. To tackle the limitations of conventional sEMG, another technique known as High-Density Surface Electromyogram (HD-sEMG) was first introduced in 1980 by Monster and Chan (1980). Recent studies have supported the need for obtaining multiple EMG signals from a specific muscle for accurate assessment of muscle excitation rather than assuming that a single EMG signal recorded using a pair of electrodes represents net muscle excitation (Vieira & Bletter, 2021). Recording HD-sEMG using electrodes as shown in Figure 4 will therefore be instrumental to analyze net muscle excitation.

In line with the large amount of data captured by HD-sEMG, the development of powerful machine learning algorithms that are capable of managing large datasets has opened a new potential in this research field to either complement or replace sEMG. The applications of machine learning for processing HD-sEMG signals have shown promising potential in previous studies, which focused on generating control signals of robotic prostheses (Boschmann & Platzer, 2014) and providing promising tools for clinical diagnosis and treatment (Lamb et al., 2020). In addition, the usage of HD-sEMG has the potential to be integrated into the fabric of clothing for enabling comfortable wearable electronic devices (Kim et al., 2020; Rojas-martínez et al., 2012).

In obtaining relevant information from raw HD-sEMG signals, feature extraction is the preliminary process of extracting valuable information (Stegeman et al., 2012). There are three categories of features that can be extracted from the measured signal, namely time-domain (TD), frequency domain (FD), and a combination of these two domains known as the time-frequency domain (TFD). Until now, various TFD analysis techniques have been developed and applied widely in other branches of engineering, such as the identification of mechanical failures (Houpis & Sheldon, 2020). However, the combination of time and frequency domains for feature extraction requires more complex computations. For TD, this method uses simpler mathematical expressions, which also result in overall good performance (Khushaba et al., 2017). As such, TD features have been commonly used in earlier studies (Mastinu et al., 2019; Sánchez-Velasco et al., 2019). TD features are calculated from the amplitudes of the individual channels of the HD-sEMG signals and do not require complex computations. Examples of TD features are Absolute Rectified Value (ARV) (Mastinu et al., 2019; Xu et al., 2018) and Root Mean Square (RMS) (Mastinu et al., 2019; Sánchez-Velasco et al., 2019). Meanwhile, FD features are calculated based on the frequency spectrum of the required signals through Fourier transformations. Mean frequency (Houpis & Sheldon, 2020; Xu et al., 2018) and median frequency (Houpis & Sheldon, 2020;
Jordanic et al., 2016) are the most commonly used FD features. A study conducted by Siddiqi and Sidek (2016) concluded that TD analysis yields higher accuracy in distinguishing different finger postures compared to FD analysis.

Classification of HD-sEMG data is essential for developing control algorithms for cybernetic prosthesis. Classification is the process of predicting the category of a set of data, such as whether the measured forearm EMG signals represent wrist flexion or extension (Houpis & Sheldon, 2020). In the absence of conventional mathematical models, it is a useful technique in modelling complex non-linear processes (Syeda Farha Shazmeen, 2013). There are three types of classification algorithms, namely supervised learning, unsupervised learning, and reinforcement learning (Siddiqi & Sidek, 2016; Syeda Farha Shazmeen, 2013). For HD-sEMG, there are three methods for classifying the signals, namely HD-sEMG activation map intensity and centre of gravity classification, HD-EMG activation map intensity classification, and single differential channel intensity classification (Gokgoz et al., 2015). All these techniques utilize supervised learning and out of these three methods, single differential channel intensity classification is the most commonly used in earlier studies (Ghazali et al., 2015; Xu et al., 2018). In this technique, the amplitude of the EMG signal is simultaneously analyzed between and within-subjects. For example, reading of the first electrode from subject 1 will be compared with first electrode from subject 2 (between-subject analysis). For within-subject analysis, reading of the first electrode from subject 1 will be compared with the rest of electrodes from the same subject (Jordanic et al., 2016).

In the earlier study by Aranceta-Garza and Conway (2019), HD-sEMG was used to classify abduction motion of the thumb and the classification process resulted in an average of 95.9% correctly classified instances. Nevertheless, the study only focuses on abduction movements, rather than flexion activities, in which normally 85% of the hand’s movements (specifically thumb) were related to thumb flexion (Zartl et al., 2014). A study by Sidek et al. (2018) focused on analyzing surface EMG signals together with ultrasound measurements during flexion of the thumb at different postures, namely at 0°, 30°, 60°, and 90°, respectively.

Conventional sEMG poses a great challenge to capture the signals from the deep compartment of the forearm. As such, an extensive analysis of EMG signals using HD-sEMG electrode patch sensor was conducted to isolate the EMG characterizations from the overall forearm signal characterizations. For transradial amputees, despite the loss of access to the intrinsic muscles, any information from the extrinsic muscles would be paramount and non-negotiable. Thus, this research is dedicated in identifying the synergies between the thumb extrinsic muscles in the set of forearm musculature to characterize the actual thumb attitudes. It is hypothesized that the existence of synergies between sEMG signal from the forearm musculature could be used to indicate various attitudes of a thumb as the only opposable digits in all hand operations in developing hand prosthesis technology for amputees.

An experimental setup was developed to capture the HD-sEMG signal from both the anterior and posterior sides of the forearm, while the thumb was flexed to various postures, namely, zero-degrees, thirty-degrees, sixty-degrees, and ninety-degrees, respectively. In each case, the amount of force exerted by the thumb in each case was 30% of the individual Maximum Voluntary Contraction (MVC). The details of the method used in collecting and analyzing the HD-sEMG signals are elaborated in the following section.

2. EXPERIMENTAL DESIGN

2.1. Research Subjects
The research has been approved by the International Islamic University Malaysia (IIUM) Research Ethics Committee (Approval ID: 2020-080). A total of 17 subjects (12 males, 5 females; age 26.5 ± 3.5 years) were randomly selected among students from the IIUM Gombak campus. Before the experiment, all subjects have read the guidelines and given their consent for
participating in this study voluntarily. The subjects were also asked to declare if they had a prior history of nerve injury, hand surgery, and/or accident on the targeted hand. The study found that none of the subjects had a previous history of such injuries.

2.2. HD-sEMG Recording Setup and Electrode Placement

64 channels of monopolar HD-sEMG signals were captured using a portable biomedical signal amplifier (Model Name: Sessantatruatto) device manufactured by OT-Bioelettronica. The 64 electrodes were arranged on an electrode pad with a grid of 13 rows by 5 columns, with an 8 mm inter-electrode distance (Part Number: GR08MM1305). A pad was placed on the anterior and posterior sides of the subject’s forearm to capture HD-sEMG signals from the forearm. The pad was located at 25% from the ulnar head and the elbow crease of the subject’s forearm patched on the anterior and posterior musculature as illustrated in Figure 5. The sampling frequency was set to 2000 Hz and a high pass filter was employed for signal processing. The total length of each subject’s forearm was calculated before the placement of the pad. This standard placement of pads is similar to what had been done in a previous study by Garza and Conway (2019).

2.2.1. Thumb Force Measurement Platform

The independent variable for this study is the angle of the thumb, which corresponds to different thumb postures. A previously developed portable thumb training system was used as shown in
Figure 6 (Sidek et al., 2018). The platform consists of a load cell that acts as a sensor to capture the force exerted by the thumb of the subject. A potentiometer was used to measure the angle of the thumb during these experiments. The adjustable wrist position was used for manipulation of the forearm at either neutral, pronation, or supination. In this study, the arm position is fixed to a neutral position while being placed on a hand rest to offer comfort to the subjects.

Figure 7 shows the angular positions of the load cell which were adjusted by the experimenter to be fixed at zero-degrees, thirty-degrees, sixty-degrees, and ninety-degrees, respectively, which correspond to a specific thumb posture. The same thumb postures have been used in a previous study by Sidek et al. (2018).

2.2.2. Experiment Setup and Data Collection
A flowchart for the data collection process is presented in Figure 8. Before the experiment commenced, the subjects were asked to read and fill up a consent form. After that, the experimenter measured the subjects’ forearm lengths individually for the electrode placement procedure. The experimenter then requested the subjects to exert their Maximum Voluntary Contraction (MVC) of thumb force. The MVC was measured by a load cell, which was integrated with a data acquisition device and a computer with MATLAB software installed. The program was written to automatically calculate the 30% MVC of each subject and generate a trajectory corresponding to the MVC values. The experimental setup used is shown in Figure 9.

The subjects were asked to sit in the upright position while facing a monitor displaying the developed Graphical User Interface (GUI). The subjects placed their forearms on the portable thumb training platform and their thumbs on the load cell. For data collection purposes, the data was first collected on the anterior side of the forearm, and subsequently the same procedure was repeated on the posterior side after the subjects had rested for 3 min.

A GUI was used to simultaneously display real-time trajectory graphs, which show both the actual thumb force being exerted by the subject, rest periods, and also the targeted amount of force, which is 30% of the MVC. An example of the trajectory for the targeted amount of force vs the actual amount of force exerted by the subjects is shown in Figure 10. For consistency, the subjects were asked to exert 30% of the MVC force three times in a single trajectory. Each 30% MVC thumb force exertion lasted for 5 seconds followed by 8 seconds of rest to prevent muscle fatigue. Three trajectories were required to be completed by the subjects for each thumb posture.

Upon completion of the first measurements for zero-degree thumb posture, the same procedure was repeated for thirty-degree, sixty-degree, and ninety-degree thumb postures, respectively. As a
result, 1224 rows of data have been collected (17 participants × 3 trials × 4 angles × 3 samples for each record × 2 windows on average × 1 hand side) in the study. However, 960 rows of data were used to classify the EMG signal, while 264 data were omitted as part of the pre-processing step since these EMG signals did not contribute to differentiate the contract and relax conditions besides exceeding ±5% tolerance of the 30% MVC force exerted. Also, the data consists of 64 columns representing 64 electrodes for each feature used. In this case, for combining ARV and RMS, the data has 128 columns.
2.3. Pre-processing Steps

2.3.1. Feature Extraction
Two time domain (TD) features which were extracted from the HD-sEMG signals recorded from the experiments, namely Root Mean Square (RMS) and Mean Absolute Value (MAV). The RMS was obtained by calculating the mean value of the EMG signal using Equation (1).

\[
RMS = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (x_k)^2}
\]  

(1)

The ARV feature is an average absolute value of the EMG signal amplitude in segmentation as shown in Equation (2).

\[
ARV = \frac{1}{N} \sum_{k=1}^{N} |x_k|
\]  

(2)
where:

“\(N\)” is the number of samples per window

“\(x_k\)” is the amplitude of the signal at the input of the amplifier (in mV)

The number of samples per window used in this experiment is 1000. As 2000 Hz was used as a sampling frequency, the RAW data epoch was 0.0005 seconds and after the feature extraction process, the epoch was 0.5 seconds.

2.3.2. Data Normalization

Since the HD-sEMG signals recorded from each subject are unique and there is also a variation of the 30% MVC value recorded among subjects, there is a need for the data to be normalized in the next pre-processing step. The normalization is important due to inter-day and inter-subject variations of the HD-sEMG signals (Bashford et al., 2020). Mathematically, the normalization of the HD-sEMG can be expressed as shown in Equation (3).

\[
\frac{n}{\bar{x}} \times 100\%
\]  

(3)

where:

“\(\bar{x}\)” is the average of all normalized data values

“\(n\)” is the data from the \(n\)th electrode out of 64 electrodes

For normalizing the data, first, the average of RMS or ARV values of all electrodes were calculated \((\bar{x})\). Then, the RMS or ARV value of the specific electrode \((n)\) was divided by the \(\bar{x}\) before being multiplied with 100 to scale up normalized values.

2.3.3. Classification

Classification is an important step in identifying patterns of HD-sEMG signals that correspond to specific thumb muscle force exertion magnitudes and postures. An open-source machine learning tool called Weka 3 was used to analyse the collected HD-sEMG data. By default, the software was set to a cross-validation fold of 10 as the test option. This implies that all input data from the HD-sEMG signal were divided into 10 groups automatically using a ratio of 1:9 (e.g., Group 1 for testing and nine other groups —Group 2 to 10 for training). After the first classification process, the testing group would be rotated (Group 2 now was meant for testing, while Group 1, Group 3 to 10 were used for training). The whole classification process took ten times indicating the 10 folds, and all 10 groups have been used for testing. The final result displayed by the Weka software is the mean of the overall 10 classification results (Frank et al., 2010). The training and testing data sets were randomly selected by Weka.

The classifiers that were selected in this study were Lazy.IBK, Random Tree, and Filtered Classifier. Lazy.IBK which is also known as the K-Nearest Neighbour (KNN) classifier uses a normalized Euclidean distance to find the closest training example to a given test section and predicts a class similar to this training sample (Moloney et al., 2021). The value of the variable \(K\) which indicates the count of nearest neighbours, can be manipulated based on the data. In this study, the \(K\) value has been set to 1 because it produced the highest correctly classified instances after comparing to other \(K\) values between 1 and 10. Data classified by a tree-based classifier, namely Random Tree, can be meaningful and easy to interpret for certain types of data. Tree-based classifiers are among the most widely used in machine learning algorithms (Frank et al., 2010; Moloney et al., 2021). Meanwhile, for Filtered Classifiers, the input data will be passed through a filter. The structure and coefficients of the filter will be based on the input and output data combination (Frank et al., 2010). In this study, the Lazy.IBK classifier has been used for
classification of the thumb postures based on anterior and posterior forearm HD-sEMG data and the resulting percentage of correctly classified instances will be analyzed and discussed.

Machine learning classification was carried out in this research such that the inputs to the machine learning algorithm were HD-sEMG data that was collected from the 64 electrodes placed on the forearm anterior and posterior muscles and the outputs were the corresponding thumb postures—zero-degrees (at rest and contract), thirty-degrees (at rest and contract), sixty-degrees (at rest and contract) and ninety-degrees (at rest and contract) which have been denoted as class A, B, C, D, E, F, and H, respectively, as shown in Table 1.

### Table 1. Denotation of thumb posture classes

| Thumb Posture                  | Class |
|-------------------------------|-------|
| Zero-Degrees (contract)       | A     |
| Thirty-Degrees (contract)     | B     |
| Sixty-Degrees (contract)      | C     |
| Ninety-Degrees (contract)     | D     |
| Zero-Degrees (at rest)        | E     |
| Thirty-Degrees (at rest)      | F     |
| Sixty-Degrees (at rest)       | G     |
| Ninety-Degrees (at rest)      | H     |

The performance characteristics utilized in this study were accuracy and precision. A brief explanation of each of these performance characteristics is as follows:

(a) **Accuracy**

The accuracy is the result of correctly classified instances. The accuracy of a model (through a confusion matrix) is calculated using the given formula below.

\[
\text{Accuracy} = \frac{TN + TP}{TN + FP + FN + TP}
\]  

(b) **Precision**

Precision tests the exactness of the relevant data collected. In case a model has high precision, it returns more significant information rather than irrelevant information.

\[
\text{Precision} = \frac{TP}{FP + TP}
\]

(c) **True Positive Rate**

True Positive Rate (TPR), also known as sensitivity, refers to the percentage of the number of correctly identified positive instances.

\[
\text{TPR} = \frac{TP}{FN + TP}
\]
3. RESULT AND ANALYSIS

The 30% MVC force exerted by each thumb at different thumb postures was recorded and tabulated in Table 2. From these results it can be seen that there was a significant variation in the magnitude of thumb force exerted by the subjects. It can also be observed that the amount of 30% MVC varied depending on the angular position of the thumb. For instance, at the ninety-degree position, the value of 30% MVC was generally higher than the value of 30% MVC at the zero-degrees position.

3.1. Statistical Analysis

Statistical analysis was run using Statistical Package for the Social Sciences (SPSS) software to test (i) correlation between the electrodes, (ii) interaction effect of hand sides, features, conditions, and angle of the thumbs on the HD-sEMG (force) data captured by the electrodes.

3.1.1. Correlation analysis

A 2-tailed Pearson product-moment correlation was run to determine the relationship between the HD-sEMG electrode readings (electrode 1 to electrode 64). As results, there were strong positive correlations within the electrodes, which were statistically significant, \( r \geq 0.859, n = 3840, p < 0.01 \).

3.1.2. Interaction effect

A Multivariate Analysis of Variance (MANOVA) was run to test the interaction effect of hand sides (anterior vs posterior), features (ARV vs RMS), conditions (contract vs relax), and angle of the thumbs (zero_degree vs thirty_degree vs sixty_degree vs ninety_degree) on the HD-sEMG readings. The result indicated a significant interaction effect of the independent variables on the dependent variables.
variables with Wilks’ Λ = 0.930, $F(192,11,229) = 1.427$, $p < 0.010$, partial $η^2 = 0.024$. That is, the hand sides, features, conditions, and angle of the thumbs contributed to the force readings captured by the HD-sEMG.

3.2. Analysis of HD-sEMG activation maps
HD-sEMG activation maps were generated based on RMS and ARV features that have been extracted from the 64 channels of HD-sEMG data. Figure 11 displays the HD-sEMG activation maps for each posture obtained from one of the randomly selected subjects (Subject 6). The information shown by the HD-sEMG activation maps indicates both the regions of muscles that had high levels of biopotential activations (high voltage) during a specific thumb force exertion and the regions of muscles that had lower biopotential activations (low voltage). Regions with higher levels of muscle activations are represented by a dark red colour, whereas regions with lower levels of muscle activation are represented by light blue and dark blue colours. It can be observed from Figure 11 that the variation in the colours presented on the HD-sEMG activation map depend on both the feature extraction method used (ARV or RMS) and also the thumb posture (zero-degrees, thirty-degrees, sixty-degrees, and ninety-degrees). The amplitude of both the RMS and ARV values...
of the signal measured from the forearm anterior side was higher compared to the posterior side for all of the postures. On the posterior side, the amplitude of both the RMS and ARV became lower as the angle of the thumb was increased. On the other hand, at the anterior side, the RMS and ARV amplitudes became higher as the angle of the thumb increased. It was also observed that the RMS feature generated higher amplitudes as compared to the ARV feature in general and this was observed in the EMG activation Maps.

### 3.3. Machine Learning for Classification of Thumb Postures from Forearm Anterior and Posterior HD-sEMG Data

Among the three classifiers which were selected to solve this classification problem, namely, Lazy.IBK, Random Tree, and Filtered Classifier, Lazy.IBK recorded the highest percentage of correctly classified instances of thumb postures with an average percentage of 96.15%, followed by Random Tree with an average percentage of 85.60% and Filtered Classifier with an average percentage of 85.54% as shown in Table 3. For brevity, only the classification results performed by Lazy.IBK will be further analyzed in this paper.

| Hand side | Feature | Correctly Classification Instances(%) |
|-----------|---------|----------------------------------------|
|           | Lazy.IBK | Random tree | Filtered Classifier |
| Anterior  | ARV      | 94.38       | 84.9         | 84.12          |
|           | RMS      | 94.79       | 81.77        | 85.94          |
| Posterior | ARV      | 97.92       | 87.71        | 84.69          |
|           | RMS      | 97.50       | 88.02        | 87.4           |
| Average   |          | 96.15       | 85.60        | 85.54          |

The following analysis involves three groups of data, namely, the anterior hand side, posterior hand side, and a combination of both anterior and posterior hand sides. Each group of data is divided into three categories. The first category consists of ARV values from the forearm anterior, the second category consists of ARV values from the forearm posterior and the third category consists of ARV values from the combination of forearm anterior and posterior data. In the second group of data, the first category consists of RMS values from the forearm anterior, the second category consists of RMS values from the forearm posterior and the third category consists of RMS values from the combination of forearm anterior and posterior data. In the third group of data, the first category consists of a combination of both ARV and RMS values from the forearm anterior, the second category consists of a combination of ARV and RMS values from the forearm posterior and the third category consists of a combination of ARV and RMS values from both the forearm anterior and posterior.

**Figure 12** demonstrates the percentage of correctly classified instances for each group of data via a bar chart for comparison purposes. By using the RMS values, data collected from the forearm posterior side recorded 97.50% of correctly classified instances, while data collected from the forearm anterior side yielded 94.79% of correctly classified instances. The results showed that the data collected from the forearm posterior achieved a higher percentage of correctly classified instances compared to data collected from the forearm anterior. The same pattern was shown by the result for feature ARV with 97.92% for forearm posterior and 94.37% for forearm anterior. Overall, features extracted from the HD-sEMG of the forearm posterior side yielded a higher percentage of correctly classified instances with an average of 97.71% for both features as compared to features extracted from forearm anterior which yielded an average of 94.58% correctly classified instances. These findings coincide with results from a previous study that revealed that data from the forearm posterior side resulted in a higher number of
correctly classified instances compared to the forearm anterior side for the classification of thumb postures (Aranceto-Garza & Arthur Conway, 2019). Classification by using a combination of data collected from both the forearm anterior and posterior sides had also been carried out. The combination of data from both hand sides utilized 64 electrodes on the forearm anterior and 64 electrodes on the forearm posterior resulting in a total data collection from 128 electrodes. The results of this combined approach showed a higher percentage of correctly classified instances compared to using data obtained from either the forearm anterior or forearm posterior only. In this combined approach using the ARV feature, results yielded a percentage of correctly classified instances of 99.48%, whereas using the RMS feature resulted in a slightly lower percentage of correctly classified instances of 98.96%. An additional analysis was also carried out which combines both the ARV and RMS features collected from both the HDsEMG from the forearm anterior and forearm posterior. This was motivated by a previous study by Siddiqi and Sidek (2016) which revealed that the percentage of correctly classified instances had increased significantly. The combination of ARV and RMS features together with both forearm anterior and forearm posterior data resulted in the highest percentage of correctly classified instances of 99.43%

3.3.1 Generation of Confusion Matrices

![Figure 12. Percentage of correctly classified instances using Lazy.IBK classifier](https://doi.org/10.1080/23311916.2022.2055445)

Correctly Classified Instances

![Correctly Classified Instances](https://doi.org/10.1080/23311916.2022.2055445)

Table 4. Confusion matrix generated when the inputs are the ARV feature data from the anterior and posterior hand sides

|          | A = zero_contract | B = thirty_contract | C = sixty_contract | D = ninety_contract | E = zero_relax | F = thirty_relax | G = sixty_relax | H = ninety_relax | TPR |
|----------|------------------|--------------------|-------------------|---------------------|--------------|-----------------|----------------|-----------------|-----|
| A = zero_contract | 120              | 0                  | 0                 | 0                   | 0            | 0               | 0              | 0               | 100 |
| B = thirty_contract | 118              | 2                  | 1                 | 1                   | 0            | 0               | 0              | 0               | 98.3|
| C = sixty_contract | 0               | 119                | 1                 | 0                   | 0            | 0               | 0              | 0               | 99.2|
| D = ninety_contract | 0               | 0                  | 2                 | 118                 | 0            | 0               | 0              | 0               | 98.3|
| E = zero_relax | 0                | 0                  | 0                 | 0                   | 120          | 0               | 0              | 0               | 100 |
| F = thirty_relax | 0                | 0                  | 0                 | 0                   | 0            | 120             | 0              | 0               | 100 |
| G = sixty_relax | 0                | 0                  | 0                 | 0                   | 0            | 0               | 120            | 0               | 100 |
| H = ninety_relax | 0                | 0                  | 0                 | 0                   | 0            | 0               | 0              | 120             | 100 |

| Precision | 100 | 100 | 96.7 | 99.2 | 100 | 100 | 100 | 100 |
Further analysis was done to investigate the characteristics of the two highest correctly classified instances (ARV and combination feature: ARV-RMS as the features and anterior-posterior as the hand side) found earlier in Figure 12. Table 4 and Table 5 show the confusion matrices, which have been generated. In Table 4, the extracted feature was ARV only, whereas in Table 5 both the ARV and RMS features were extracted as used as inputs for the classification.

From both the confusion matrices presented in Table 4 and Table 5, it can be observed that the algorithm accurately predicts all the classes E, F, G, and H (which correspond to various thumb postures) when the thumb is at rest. Similarly, for class A, which corresponds to the thumb being at zero-degree in contract condition, the algorithm accurately predicts this class as well. However, a few instances of misclassification can be seen in both Table 4 and Table 5. The misclassification occurs during the classification of classes B, C and D while simultaneously exerting 30% MVC (in contract condition). In Table 4, it can be observed that data that was supposed to belong to class B were incorrectly classified as belonging to class C during two instances. Data that was supposed to belong to class C was incorrectly classified as belonging to class D during one instance. Data that was supposed to belong to class D was incorrectly classified as belonging to class C during two instances. A similar pattern of misclassification during the classification of classes B, C, and D can also be seen in Table 5. Overall in Table 4, it can be seen that there is a total of 5 incorrectly classified instances out of 960 (99.48%), whereas in Table 5 there is a total of 11 incorrectly classified instances out of 1920 (99.43%).

4. CONCLUSION
The primary goal of this research study was to investigate the HD-sEMG signals from the forearm area that vary according to different thumb postures. The features extracted from the recorded signals were the ARV and RMS. Classification was then performed using the Lazy.IBK classifier. The overall result shows that correctly classified instances are above 90%. It can be concluded that although thumb postures can be accurately classified by using HD-sEMG signals from either the forearm anterior or posterior alone, the best results are obtained when a combination of HD-sEMG data collected from both the forearm anterior and posterior together with using the ARV as the extracted feature as input to the machine learning algorithm. Since both hand sides (anterior and posterior) consist of muscles that contribute to controlling thumb attitude, findings in the study are important for a better development of prosthetic hands. Future studies might consider including transradial amputees as test subjects to increase the robustness of the developed system.
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Endnotes
1. https://www.ibm.com/products/spss-statistics

Disclosure statement
No potential conflict of interest was reported by the author(s).

References
Physiopedia contributors. “Abductor pollicis LongusPhysiopedia.” https://www.physio-pedia.com/Abductor_pollicis_longus?utm_source=physio-pedia&utm_medium=search&utm_campaign=ongoing_internal (accessed Jun. 07, 2021)

Physiopedia contributors. “Extensor Pollicis LongusPhysiopedia.” https://www.physio-pedia.com/Extensor_Pollicis_Longs (accessed Jun. 07, 2021)

Adewuel, A. A., Hargrove, L. J., & Kuklen, T. A. (2016). An Analysis of Intrinsic and Extrinsic Hand Muscle EMG for Improved Pattern Recognition Control. IEEE, Trans. Neural Syst. Rehabil. Eng, 24(4), 485–494. https://doi.org/10.1109/TNSRE.2015.2424371

Aranceta-Garza, A., & Arthur Conway, B., Differentiating Variations in Thumb Position From Recordings of the Surface Electromyogram in Adults Performing Static Graps, a Proof of Concept Study Frontiers in Bioengineering and Biotechnology, 71 1–11 2019 https://doi.org/10.3389/fbioe.2019.00123

Bashford, J., Wickham, A., Iniesto, R., Drakakis, E., Boutelle, M., Mills, K., & Shaw, C. E. (2020). Clin. Neurophysiol Preprocessing surface EMG data removes voluntary muscle activity and enhances SPOE fascilitation analysis. Clin. Neurophysiol, 131(1), 265–273. https://doi.org/10.1016/j.clinph.2019.09.015

Boschmann, A., & Platzner, M., “Towards Robust HD EMG Pattern Recognition : Reducing Electrode Displacement Effect using Structural Similarity,” 2014 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., pp. 4547–4550, 2014.

Chowdhury, R. H., Reaz, M. B. I., Ali, M. A. B. M., Bakar, A. A., Chellappan, K., & Chang, T. G. (2013). Surface Electromyography Signal Processing and Classification Techniques (pp. 12431–12466). https://doi.org/10.3390/130912431

Cronin, N. J., Kumpulainen, S., Joutjärvi, T., Finni, T., & Piitulainen, H. (2015). Spatial variability of muscle activity during human walking: The effects of different EMG normalization approaches. Neuroscience, 300, 19–28. https://doi.org/10.1016/j.neuroscience.2015.05.003

Dupan, S. S. G., Stegeman, D. F., & Moas, H. (2018). Distinct neural control of intrinsic and extrinsic muscles of the hand during single finger pressing. Hum. Mov. Sci, 59(April), 223–233. https://doi.org/10.1016/j.humov.2018.04.012

Enoka, R. M. (2019). Physiological validation of the decomposition of surface EMG signals. J. Electromyogr. Kinesiol, 46(September), 70–83. https://doi.org/10.1016/j.jelekin.2019.03.010

Flexor Pollicis Longus “Flexor Pollicis Longus - Physiopedia.” https://www.physio-pedia.com/Flexor_Pollicis_Longs?utm_source=physio-pedia&utm_medium=search&utm_campaign=ongoing_internal (accessed Jun. 11, 2021)

Frank, E., Hall, M., Holmes, G., Kirkby, R., & Witten, I. H. (2010). Data Mining and Knowledge Discovery Handbook. Data Min. Knowl. Discov. Handb, (July), 0–10. https://doi.org/10.1007/978-0-387-09823-4

Ghazali, A. S., Sidek, S. N., & Wor, S. (2015). Affective state classification using Bayesian classifier. Proc. - Int. Conf. Intell. Syst. Model. Simulation, SIMS, 2015, 154–158. https://doi.org/10.1109/SIMS.2014.32

Gokgoz, E., & Subasi, A. (2015). Comparison of decision tree algorithms for EMG signal classification using DWT. Biomedical Signal Processing and Control, 18, 138–144. https://doi.org/10.1016/j.bspc.2014.12.005

Houpis, C. H., & Sheldon, S. N. (2020). Frequency Domain Analysis. Linear Control Syst. Anal. Des. With MATLAB, 63–70. https://doi.org/10.1201/b16032-7

Il Park, W., Kwon, S., Lee, H. D., & Kim, J. (2012). Real-time thumb-tip force predictions from noninvasive biosignals and biomechanical models. Int. J. Precis. Eng. Manuf, 13(9), 1679–1688. https://doi.org/10.1007/s12541-012-0220-2

Jabir, S., Lyall, H., & Iwugwu, F. C. (2013). The extensor pollicis brevis: A review of its anatomy and variations. Eplasty, 13, e35.

Jordán, M., Rojas-martinez, M., Mañanos, M. A., Alonso, J. F., Schneider, E., Strupp, M., & Kolla, R. (2016). Spatial distribution of HD-EMG improves identification of task and force in patients with incomplete spinal cord injury. J. Neurorehab. Rehabil, 3, 1–11. https://doi.org/10.1186/s12984-016-0151-8

Khushaba, R. N., Al-Timemy, A. H., Al-Ani, A., & Al-Jumaily, A. (2017). A Framework of Temporal-Spatial Descriptors-Based Feature Extraction for Improved Myoelectric Pattern Recognition. IEEE, Trans. Neural Syst. Rehabil. Eng, 25(10), 1821–1831. https://doi.org/10.1109/TNSRE.2017.2687520

Kim, S., Lee, S., & Jeong, W. (2020). EMG measurement with textile-based electrodes in different electrode sizes and clothing pressures for smart clothing design optimization. Polymers (Basel), 12(10), 1–13. https://doi.org/10.3390/polym12102406

Lamb, L. et al. (2020). MP07-15 NATIONAL COLLABORATIVE CROWD SOURCING METHOD OF Copyright © 2020 American Urological Association Education and Research, Inc. Unauthorized reproduction of this article is prohibited . Copyright © 2020 American Urological Association Education and, 203(4), 102–103.

Maduri, P., & Akhandi, H. (2020). Upper Limb Amputation. StatPearls. StatPearls Publishing, Treasure Island (FL) Treasure Island.

Mastini, E. et al. (2019). Grip control and motor coordination with implanted and surface

Page 17 of 19
electrodes while grasping with an osseointegrated prosthetic hand Journal of NeuroEngineering and Rehabilitation. 2, 1–10. doi:10.1186/s12984-019-0511-2.

Moloney, D. et al. (2021). DETECTING K-COMPLEXES FOR SLEEP STAGE IDENTIFICATION USING NONSMOOTH OPTIMIZATION. 52 (2011), 319–332. https://doi.org/10.1017/S1446181112000016

Phinyomark, A., Phukpattaranont, P., & Limsakul, C. (2012). Expert Systems with Applications Feature reduction and selection for EMG signal classification. Expert Syst. Appl., 39(8), 7420–7431. https://doi.org/10.1016/j.eswa.2012.01.102

Phinyomark, A., Thongpanja, S., Quaine, F., & Laurillau, Y. (2013). “Optimal EMG Amplitude Detectors for Muscle-Computer Interface,” no 2013 10th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology. IEEE. 1–6. https://doi.org/10.1109/ECTICon.2013.6559485

Rojas-martínez, M., Mañanas, M. A., & Alonso, J. F. (2012). High-density surface EMG maps from upper-arm and forearm muscles. 1–17.

Sánchez-Velasco, L. E., Arios-montiel, M., Guzman-ramirez, E., & Lugo-gonzález, E. (2019). A Low-Cost EMG-Controlled Anthropomorphic Robotic Hand for Power and Precision Grasp. Biocybern. Biomed. Comput. 40 1 (pp. 221–237 0208-5216). https://doi.org/10.1016/j.bmc.2019.10.002

Siddiqi, A. R., & Sidek, S. N. (2016). Estimation of continuous thumb angle and force using electromyogram classification. Int. J. Adv. Rob. Syst, 13(5), 1–12. https://doi.org/10.11077/1729881416658179

Sidek, S. N., Roslan, M. R., Sidek, S., & Khalid, M. S. M. (2018). Thumb-tip force prediction based on hill’s muscle model using electromyogram and ultrasound signal. Int. J. Comput. Intell. Syst, 11(1), 238–247. https://doi.org/10.2991/ijcis.11.1.18

Stegeman, D. F., Kleine, B. U., Lopatki, B. G., & Johannes P. V. D. (2012). High-density Surface EMG: Techniques and Applications at a Motor Unit Level. Biocybern. Biomed. Eng, 32(3), 3–27. https://doi.org/10.1016/S0208-5216(12)70039-6

Syeda Farha Shazneen, S. F. S. (2013). Performance Evaluation of Different Data Mining Classification Algorithm and Predictive Analysis. IOSR J. Comput. Eng, 10(6), 1–6. https://doi.org/10.9790/0661-106016

Vieira, T. M., & Botter, A. (2021). The Accurate Assessment of Muscle Excitation Requires the Detection of Multiple Surface Electromyograms. Exerc. Sport Sci. Rev, 49(1), 23–34. https://doi.org/10.1249/JES.000000000000240

Wijk, U., & Carlsson, I. (2015). Forearm amputees’ views of prostheses use and sensory feedback. J. Hand Ther, 28(3), 269–278. https://doi.org/10.1016/j.jht.2015.01.013

Willem Monster, A., & Chan, H. (1980). Surface electromyogram potentials of motor units; Relationship between potential size and unit location in a large human skeletal muscle. Exp. Neurol, 67(2), 280–297. https://doi.org/10.1016/0014-4886(80)90230-7

Xu, W. F., Fang, Y. F., Zhang, G. Y., Ju, Z. J., Li, G. F., & Liu, H. H. (2018). Surface EMG Channel Selection for Thumb Motion Classificationsignal. Proc. - Int. Conf. Mach. Learn. Cybern, 2, 662–666. https://doi.org/10.1109/ICMLC.2018.8526988

Yan, L. et al. (2019). Thumb Amputations Treated With Osseointegrated Percutaneous Prostheses With Up to 25 Years of Follow-up. Wolters Kluwer Heal. Acad. Orthop. Surg, https://doi.org/10.5435/JAAOSGlobal-D-18-00097

Zarti, M., Kapfer, T., & Muehlbacher, W. (2014). Functional topography of cortical thumb movement representations in human primary motor cortex. Brain Topography, 27(2), 228–239. https://doi.org/10.1007/s10528-013-0289-7

Ziegler-graham, K., Mackenzie, E. J., Ephraim, P. L., Travison, T. G., & Brookmeyer, R. (2008). Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050. 89(March), 422–429. https://doi.org/10.1016/j.ajpmr.2007.11.005
