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RESEARCH PAPER

Deep convolution neural network to improve hand motion classification performance against varying orientation using electromyography signal (Arial 22, BOLD, JUSTIFY)

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ABSTRACT (ARIAL 10, BOLD)

(ARIAL 10, BOLD) High accuracy and fast computation time are essential in the implementation of hand gesture pattern recognition for prosthetic hand using electromyography (EMG) signal. However, there are several physical parameters that affect the characteristics of the EMG signal, including forearm orientation. Therefore, this study aims to develop a deep learning classifier using convolution neural network (CNN) algorithm which maintains accuracy with changes in the forearm orientation. The contribution made was the development of the proposed CNN method without using a feature extraction process to recognize the EMG patterns. Furthermore, the proposed training scheme able to maintain the accuracy against the orientation changes. This method consists of a two-dimensional convolution, max-pooling, four fully connected and output layer. The input layer classifier received six channels of raw EMG signal derived from ten able bodies. As a comparison, several conventional classifiers including support vector machine, K-nearest neighborhood, linear discriminant analysis and decision tree were applied to examine the performance among the classifiers. Furthermore, the consistency of the classifier accuracy was tested using the orientation dataset 1, 2, 3 and the combination of all orientation's dataset. The result showed that the accuracy of the proposed CNN classifier based on all orientation was 96.8±1.87%. Furthermore, the difference in accuracy among the orientations was less then 5%. This indicates that the classifier is able to maintain high accuracy with changes in orientation. In conclusion, this study is applicable in the development of prosthetic hands using EMG signal as control with constant accuracy when the forearm orientation varies.

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1. INTRODUCTION (ARIAL 10, BOLD, H1)

(ALL Arial 10) The recognition of electromyography (EMG) patterns is essential in the development of rehabilitation devices or systems that support the use of EMG signal as control [1]. This signals are widely used because they are easily recorded and respond faster compared to other mechanical sensors [2]. However, the EMG signal has random characteristics and is influenced by many parameters [3][4]. Therefore, it requires precise pre-processing and pattern recognition. Furthermore, in the development of prosthetic hands for amputees, the correct recognition of hand gestures through EMG signals is crucial [5]. This enables the artificial hand mimic the actual movement[1]. In addition, the selection

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of the right classifier to recognize the EMG patterns is essential as it determines the accuracy of the system being developed. Currently, several studies have developed deep learning based classifier with the convolution neural network (CNN) algorithm to solve problems in pattern recognition based on EMG signal [6][7][8]. The advantage of this algorithm is that the classifier does not require feature engineering or extraction to recognize EMG signal patterns. However, several factors affect the EMG signal parameters (such as frequency and amplitude) in the development of rehabilitation devices. These factors include muscle fatigue [9], force variation [10], and forearm orientation [11].

In this study, the forearm orientation was a concern, because its effect needs to be anticipated in the prosthetic hand implementation, in order to determine whether it affects the accuracy of the classifier or not. Several previous studies have developed hand gesture recognition through EMG signals by considering the forearm orientation towards classifier accuracy. Furthermore, Khushaba et al. studied the effect of muscle contraction and forearm orientation (three orientations) on the accuracy of five hand gestures [11]. Meanwhile, in this study, the EMG signal was extracted using time domain and power spectrum descriptor (TD-PSD). However, based on the proposed method by TD-PSD and SVM classifier, the accuracy obtained ranged from 85% to 93%. This varied for training and testing using all orientation and contraction. Other studies explored the effect of the forearm position (five positions) on the accuracy of the pattern recognition for eight classes [12]. The time domain feature was used to extract the EMG signal and linear discriminant analysis (LDA) was used as a classifier. The results showed that there was significant decrease in accuracy when the classifier was trained in all positions with an average accuracy of 95%. However, the results showed that the accuracy of each class varied which ranged from 70%-91% using the training and testing scheme of all positions. Furthermore, Yanjuan et al developed hand gesture recognition using EMG signal and accelerometer on amputee, using standard time domain feature and LDA [13]. The results showed that the error value obtained was 29.9 ± 3.2%. In addition to the conventional classifier, several studies have developed deep learning to recognize hand gesture using EMG signals [6][7]. However, the effect of orientation on classifier accuracy has not been considered. In addition, several previous studies have not revealed the computation time required to carry out the classification process. Meanwhile, the computation time is essential when the model is implemented in embedded systems.

Previous studies which discussed the effect of dynamic forearm positions on classifier accuracy, implemented conventional classifiers (LDA and SVM) and standard time domain (TD) features to develop pattern recognition models for hand gesture recognition using EMG signals [13] [14] [15][16]. The implementation of TD feature for pattern recognition operations was recommended by several studies due to its fast computation time [17][18] [19] [20]. However, an in-depth investigation is needed regarding the selection of the right TD features and classifiers, to obtain good accuracy in the developed system. This investigation is time consuming and requires its specific study. Therefore, a deep learning approach with convolution neural network (CNN) algorithm is a solution to pattern recognition with non-feature engineering (without hand craft feature extraction). Furthermore, several previous studies have developed hand gesture patterns recognition through EMG signals with a variety of forearm orientations [11][13][14][21]. However, the predicted gesture had a fairly large difference in accuracy (p-value <0.05) when the classifier training-testing used the dataset of all orientations and gestures. Therefore, a proper training and testing scheme is essential to increase the accuracy of the classifier. This maintains accuracy when the classifier is randomly tested with data from other orientations.

Therefore, to solve this problem, this study aims to develop a deep learning-based classifier architecture with convolution neural network (CNN) algorithm against changes in forearm orientation through six channel EMG signals. The contributions of this study are 1) the developed CNN classifier does not require the feature extraction stage. Instead, it processes the data directly using the raw EMG signal, 2) the developed CNN classifier is able to produce same accuracy when the classifier is tested using gestures from different orientations, 3) a simple CNN classifier architecture is produced, therefore enabling the computation time of the pattern recognition process to be within the tolerable limit to build a real-time system. To achieve this, the EMG signal was segmented by a certain batch number. Furthermore, the two-dimensional CNN architecture and hyper parameter were investigated to produce good classifier accuracy. In addition, this study proposed a training and testing scheme originating from all orientations and contractions to enable the CNN classifier be robust against orientation changes.

This study is structured as follows: section II discusses the dataset used, proposed methods and proposed training and testing schemes. Section III displays the results of CNN accuracy and responses to forearm orientation. Section IV discusses the interpretation and comparison of results with other studies and limitations. Section V, conclusions, which rewrite the objectives, main findings and future works.

2. MATERIALS AND METHOD (ARIAL 10, H1)

A. Dataset (Arial 10, Bold, H2)

(Arial 10) This study aims to examine whether there is a significant difference in accuracy when the orientation

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position is different. The three types of orientation used were wrist fully supinated, at rest, and fully pronated, each marked as 1, 2 and 3 orientation as shown in Fig. 1. The EMG signal was recorded using a Bagnoli EMG recorder (Delsys, Massachusetts, USA) with sampling frequency of 4,000 Hz. Afterwards, six pairs of electrodes marked 1 to 6 were placed equidistant on the forearm (Fig. 1). The dataset used in this study was obtained from 10 subjects with normal body condition and non-amputee. The data collection followed ethical clearance procedures as standard of measurement to the human. In these procedures, each subject performed hand gesture movements with three different orientations. In addition, each orientation consists of seven basic movements with each consisting of three levels of contraction (low, medium and high). Furthermore, each level of contraction consisted of three trials. The motion that will be recognized in this study are hand close (C1), hand open (C2), wrist extension (C3), wrist flexion (C4), wrist ulnar deviation (C5), wrist radial deviation (C6), and relax (C7). The public dataset used in this study is open access and can be found at the following link.

Fig. 1. The implementation of deep learning using two-d min 10 words, justify): AUTHOR MUST USE A TEXT BOX F

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B. Data Collection (Arial 10, BOLD, H2)

(Arial 10) EMG signals were recorded for approximately 5 seconds or about 20,000 data for every single hand gesture movement. In addition, the subjects were given 10 seconds of rest to prevent the effect of muscle fatigue after each contraction, during data collection. An example of the EMG signal recording dataset is illustrated in Fig. 1. It shows the experiment protocol to collect the EMG signal from one orientation, sequentially. In detail, the number of EMG data for 1 subject and 1 orientation is 1,260,000 (1 orientation x 7 motion x 3 contraction level x 3 trials x 20,000 data). Before being fed to the CNN classifier, the EMG signal was segmented with a window length of 500 samples or 125 milliseconds (fsampling = 4,000 Hz, tsampling = 0.25

C. Data Processing (Arial 10)

It can be calculated using Eq. (1) as follows [24]:

$$S(i,j) = (K * I)(i,j) = \sum_{m}\sum_{n} I(i-m, j-n)K(m,n) \tag{1}$$

where S (i, j) is a feature map resulting from the convolution between kernel K (m, n) and input feature I (i, j). The output-shape after the 2D convolution process with a 2D kernel can be calculated using equation (2), as follows [25] [24]:

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$$o = \frac{(w - f + 2p)}{s} + 1 \quad (2)$$

where o, w, f, p, and s are the output shape, input shape, kernel length, and stride, respectively. In the input section, CNN performs a convolution process between 2D kernel and 2D input. This is repeated to produce a features map on the filter

3. RESULTS (ARIAL 10, BOLD, H1)

A. Accuracy (Arial 10, BOLD, H2)

(Arial 10) The accuracy of all classifiers from both the proposed method (CNN) and the comparison classifier (KNN, SVM, LDA and DT) was calculated for all orientation types (1, 2 and 3). Classifier accuracy was obtained from 10 subjects involved. In this study, the results of the classifier accuracy were displayed using the box plot diagram of descriptive statistics. It is used to visualize the mean and quartile of accuracy values. Fig. 4 shows a comparison of the boxplot accuracy diagrams of the CNN, KNN, SVM, LDA and DT classifiers for all orientation types (1, 2, and 3). The CNN classifier has the highest accuracy (99.3 ± 0.82%, orientation 1) followed by KNN and DT. However, in this case, the SVM classifier produced the worst performance (56.35 ± 10.20%) in the classification process. The comparison of accuracy based on orientation showed that type 1 was the highest for all classifier types followed by orientation types 2 and 3.

B. Performance (Arial 10, BOLD)

(Arial 10) In order, the classifier recognized 7 hand gestures for all orientation types and all force levels. Furthermore, three datasets from orientations 1, 2 and 3 were combined and randomized for the training and testing process, which was referred to as scheme 4. Fig. 5 shows that the CNN classifier still produces the best accuracy (96.80 ± 1.87%) compared to other classifiers after the combined process of 3 orientation datasets. Fig. 4 shows a comparison of the boxplot accuracy diagrams of the CNN, KNN, SVM, LDA and DT classifiers for all orientation types (1, 2, and 3). The CNN classifier has the highest accuracy (99.3 ± 0.82%, orientation 1) followed by KNN and DT. However, in this case, the SVM classifier produced the worst performance (56.35 ± 10.20%) in the classification process. The comparison of accuracy based on orientation showed that type 1 was the highest for all classifier types followed by orientation types 2 and 3. Fig. 4 shows a comparison of the boxplot accuracy diagrams of the CNN, KNN, SVM, LDA and DT classifiers for all orientation types (1, 2, and 3). The CNN classifier has the highest accuracy (99.3 ± 0.82%, orientation 1) followed by KNN and DT. However, in this case, the SVM classifier produced the worst performance (56.35 ± 10.20%) in the classification process. The comparison of accuracy based on orientation showed that type 1 was the highest for all classifier types followed by orientation types 2 and 3. Fig. 4 shows a comparison of the boxplot accuracy diagrams of the CNN, KNN, SVM, LDA and DT classifiers for all orientation types (1, 2, and 3).

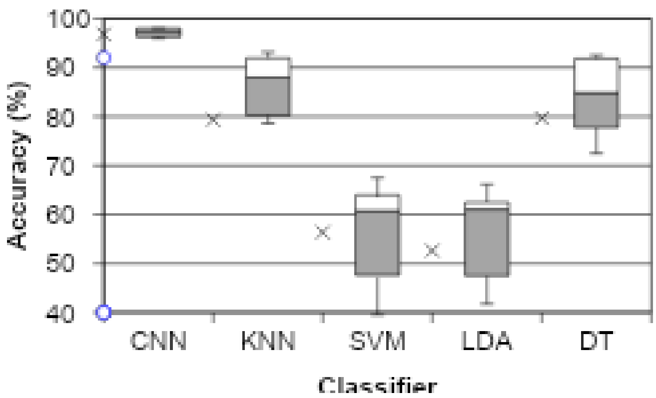

Fig. 5. The boxplot of descriptive statistics to compare the mean accuracy among the classifier for the combination of three orientation and three contraction levels. (Arial 10, Bold, min 10 words, justify)

Table 1 (coloring with dark blue for Table, Figure and Equation) shows the classifier accuracy (mean and standard deviation) for scheme 4. The CNN classifier had the highest accuracy (96.80 ± 1.87%) and lowest standard deviation (± 1.87%) compared to other classifiers.

Table 2 shows the differences and significant different among the accuracy from different orientation. The comparison of the mean accuracy of scheme 4 against schemes 2 and 3 showed that there was no significant difference (4-2 difference: -1.7%, p = 0.121; 4-3 difference: -0.4%, p = 0.949). However, there was a significant difference when the mean accuracy of scheme 4 compared to scheme 1 (4-1 difference: -2.5%, p = 0.010). The comparison of the mean accuracy of scheme 4 against schemes 2 and 3 showed that there was no significant difference (4-2 difference: -1.7%, p = 0.121; 4-3 difference: -0.4%, p = 0.949). However, there was a significant difference when the mean accuracy of scheme 4 compared to scheme 1 (4-1 difference: -2.5%, p = 0.010).

Table 1. The classifier accuracy (mean and standard deviation) to recognize the seven hand gesture from ten subjects when the data is combined from all type orientation and all contraction. (Arial 10, Bold, min 10 words)

Classifier	Mean (%)	SD (%)
CNN	96.80	±1.87
KNN	79.35	±25.73
SVM	56.36	±10.2

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LDA	52.62	±17.11
DT	79.67	±18.69

4. DISCUSSION (ARIAL 10, BOLD, H1)

A. Classifier (Arial 10, BOLD, H2)

(Arial 10) This study aims to reveal whether there is a significant difference in accuracy when the classifier is tested to recognize 7 gestures using various types of orientation (orientations 1, 2, 3 and all). The results of this study showed that there is a slight decrease in the mean accuracy among scheme 4 against schemes 1, 2 and 3 by (difference 4-1:0.41%, difference 4-2:1.75%, and difference 4-3: 2.58%, respectively). produced by the KNN, SVM, LDA, and DT with values of ± 25.73%, ± 10.2%, ± 17.11%, and ± 18.69%, respectively.

In addition as shown in Fig. 6, the higher accuracy for orientation types 1 and 2 were also in line with the results of study by Rami Khushaba et al. The variations in the accuracy results obtained ranged from 48.6% to 96.6% (mean = 74.8%) for all combinations of training and orientation testing (1, 2 and 3) [11]. Conversely, a decrease in classifier accuracy was also experienced by a study proposed by Yanjuan et al, which examined the effect of the limb position (5 positions) on the classification results. The resulting average accuracy value is ~ 90% [13].

Fig. 6. The boxplot of descriptive statistics to compare the mean accuracy among the classifier for the combination of three orientation and three contraction levels. (Arial 10, Bold, min 10 words, justify)

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This indicates that the CNN classifier is able to classify 7 gestures for various types of orientation with low difference in accuracy between orientations (<5%). Furthermore, the single-factor ANOVA statistical test based on Tukey HSD showed that there is no significant difference in accuracy (p-value> 0.05) between the training-testing scheme 4 vs 2, 4 vs 3, 1 vs 2, and 2 vs 3. However, several tests between groups showed that there was a significant difference in accuracy (p-value <0.05) for the scheme group 1 vs 4 and 1 vs 3. This is because, the difference in mean accuracy for the two groups was larger compared to the others (1-4 difference: 2.5% and 1-3 difference: 2.1%). However, the differences are tolerable (<5%). Furthermore, the mean value of accuracy obtained was quite high (96.80 ± 1.87%) when the classifiers were trained and tested using scheme 4. This explains that even though all datasets with three different orientation types were combined, the CNN classifier still showed maximum accuracy. The low standard deviation (1.87%) indicates that most of the resulting accuracy values have almost centered accuracy at 96%. This was different, when accuracy is compared with the standard deviation

B. Confusion matrices

The single factor ANOVA statistical test using Tukey HSD on the results of the confusion matrices (Fig. 7) for Post Hoc multiple comparisons showed that there was no significant difference in accuracy (p-value> 0.05) for comparisons between all gestures in the scheme 4. This proved that the proposed classifier (CNN) has the same accuracy for all predicted gestures (7 gestures). In training and testing scheme (4), it is revealed that the resulting accuracy for recognizing gestures (1 = hand open) was the lowest (83.53 ± 10.51%). This low accuracy is because the subject carries out gesture 1, which includes the open position, possibility of each repetition of the open condition is different, causing different EMG records. The low accuracy of gestures (1 = open) is also in line with the results of the study carried out by Khushaba et al, which obtained the lowest accuracy in gestures (1 = hand open) at 84.0% [11].

5. CONCLUSION (ARIAL 10, BOLD, H1)

(Arial 10) This study aims to develop a classifier by classifying 7 gestures that are robust against variations

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of forearm orientation. The result showed that the accuracy of the CNN algorithm outperformed other comparison classifiers (SVM, KNN, LDA, and DT) ($p<0.05$). There was a decrease in CNN accuracy (<5%) which resulted from the difference from scheme 4 (combination of all orientation) to scheme 1, 2, and 3. Furthermore, multiple comparisons using Tukey HSD (alpha = 0.05) revealed that 4 out of 6 groups showed that there was no significant difference in accuracy (p-value> 0.05). The computation time of the proposed CNN was still within the recommended tolerance limit (<200ms). In conclusion, further studies related to the implementation of CNN in embedded systems should be proposed to develop a prosthetic hand that is robust against orientation.

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AUTHOR BIOGRAPHY (ARIAL 10, BOLD, H1)

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