Journal of Physics: Conference Series

PAPER • **OPEN ACCESS**

Investigation of the Number of Features and Muscles for an Effective Hand Motion Classifier Using Electromyography Signal

Investigation of the Number of Features and Muscles for an Effective Hand Motion Classifier Using Electromyography Signal

Triwiyanto Triwiyanto*, Bedjo Utomo, Dyah Titisari, M. Ridha Mak'ruf, Triana Rahmawati

Department of Electromedical Engineering, POLTEKKES KEMENKES Surabaya
Jl. Pucang Jajar Timur No. 10, Surabaya, Indonesia.

*Email: triwiyanto123@gmail.com

Abstract. The essential problem in the development of a prosthetic hand based on electromyography (EMG) signal is the choice of the features and number of muscles that will be used to recognize the hand motion. A minimal number of feature and channel could reduce the cost in the development of the prosthetic hand and processing time. Therefore, it is important to obtain the correct number of feature and muscles in the system. The objective of this study is to evaluate the effectiveness of using the number of feature and muscle to recognize the hand motion for amputee person using the EMG signal. In this study, the EMG dataset was obtained from five transradial amputee persons. Ten disposable electrodes (Ag/AgCl) were placed on the residual hand with equal space between the electrodes. In order to obtain the EMG features which are related to the hand motion, each of the EMG signal was extracted using six-time domain features which are root mean square (RMS), integrated EMG (IEMG), waveform length (WL), difference absolute standard deviation value (DASDV), Wilson amplitude, and myopulse rate (MYOP). Each feature was evaluated using Decision Tree, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K- nearest neighborhood, and Ensemble machine learning (ML). The number of class to be classified in this study was eighteen motions. The effectiveness of using the number of features and muscles was evaluated by varying the number of features and muscles. Further, the accuracy, in the discrimination of the motion, was calculated and compared among the machine learnings. The results of this study show that six muscles can effectively classify the eighteen of hand motion. The ML with WL feature has the highest accuracy among the others (81.3% based on quadratic SVM). The study suggested the effective number of muscle and feature which can be used in the prosthetics hand development so that the effective prosthetic machine can be built with a low cost in the time computing and the hardware for data acquisition.

1. Introduction

Forty-one thousand people in the USA had to lose their hand due to work accident and cancer disease [1]. In this case, an amputation had to be taken, and this condition could limit their work and influence their social activity. Some prosthetics devices have been developed to substitute the hand function by controlling the devices using EMG signal or mechanical sensors such as accelerometer-gyroscope or inertial sensor. However, because of the lack of functionality, some of the users abandoned the devices. Recently, the EMG signal has been used a lot as a control signal for assistive exoskeleton devices [2] [3] [4], electronic prosthetics [5] [6] [7] and teleoperation [8] because the response is faster than the mechanical sensors [9]. However, the EMG signal has complex, non-linear and stochastics characteristics in nature [10]. Even though the EMG signal is generated from the same electrode's location, motion, and person, it will generate a different pattern for every time of measurement [10]. Previous studies had been investigated the behavior of the EMG signal in accordance with the human motion and it was found that the EMG signal (amplitude) is related to human limb (upper and lower) motion [11].

Feature extraction plays an important role to obtain the relation between human limb motion and the EMG signal. Feature extraction is classified into three domains, those are time, frequency and time-frequency domain (wavelet) [12]. The feature extraction based on frequency and time-frequency domain needs more computation time than time domain because it needs a transformation between domain. Therefore, features extraction which uses time domain is often used by previous studies. Generally, time-domain feature extraction is divided into four categories; those are based on energy (such as RMS, IEMG, MAV), complexities (WL, AAC, DASDV), frequency (ZC, MYOP, WAMP, SSC) and statistics (mean, kurtosis, maximum, minimum, skewness). Each feature has a different response for each type of motion. Therefore, an investigation of the time domain features which related the hand motion is important in order to find the best feature. In order to discriminate the type of hand motion, previous studies have investigated several EMG features to discriminate some type of hand motion for a transradial amputee. However, majority, previous studies only proposed a method to discriminate two (open and close) [7], four (open/close and supination/pronation) [13] to eight (wrist flexion, wrist extension, pronation, supination, power grip, pinch grip, open hand, and rest) [14] type of hand motions. By considering that the higher number of class then the complexities of the EMG signal will increase and also it will reduce the accuracy of the machine learning. However, a more complex hand motion is needed in order to get a prosthetics hand which is able to imitate the real hand for an amputee. A study of hand motion for complex motion has been developed to discriminate seventeen motions [15]. However, in those work, the twelve of electrode pairs has to be placed in order to discriminate the seventeen motions. In the development of the prosthetics hand, it is still a challenging study, to develop a prosthetic device with a minimum number of electrodes, in order to minimize the size of the amplifier unit and reduce the digital signal processing computation. Furthermore, machine learning is needed to encode the EMG features which are related to the hand motion. Generally, standard machine learning such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and K-NN were used by previous studies to discriminate the hand motion [16]. However, those machines learning used is based on a linear approach. On the other hand, the EMG signal has non-linear, random and stochastic characteristics in nature [10]. Therefore, some ML with a non-linear kernel was needed to be investigated in order to find the fittest model to recognize the hand motion. Therefore, in this study, the 22 of ML was investigated. Those ML are Fine Decision Tree, Medium Decision Tree, Coarse Decision Tree, Linear Discriminant Analysis, Quadratic Discriminant Analysis, Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM, Fine KNN, Medium KNN, Coarse KNN, Cubic KNN, Weighed KNN, and Ensemble (such as: boosted tree, bagged tree, subspace discriminant, subspace KNN, RUS–Boosted tree).

Based on the problems that have been mentioned, consequently, the objective of this study is to investigate the performance of the twenty-two machine learnings with an approach to the quadratic, cubic, fine, medium, and coarse kernel to classify the eighteen type of hand motion based on the EMG signal from amputee person. Special aims of this study are 1) to investigate the effective number of muscles to predict the eighteen type of hand motion (including in rest condition), 2) to investigate the best EMG feature to recognize the eighteen type of hand motion. The impact of this study is toward an effective hand motion classifier so that in the future this proposed method can be used for the development of the hand prosthetics with minimum number of muscle and less computation.

2. Materials and Methods

2.1. Participant

In this study, the EMG signal (**Figure 1**) was obtained from Ninapro dataset db3 (http://ninapro.hevs.ch) which was collected from five amputee persons who have an amputation after the accident. The EMG signal was recorded using twelve electrodes (Trigno Wireless electrodes, Delsys, Incorporation, www.delsys.com). The eight electrodes were placed on the residual hand with equal spaces, two electrodes were located on the extensor carpi and flexor carpi which are the most responsible muscle in the hand motion [17]. The two other electrodes were also positioned on the biceps and triceps muscles. The preparation procedures and the placement of the electrodes have followed the SENIAM rules [18].

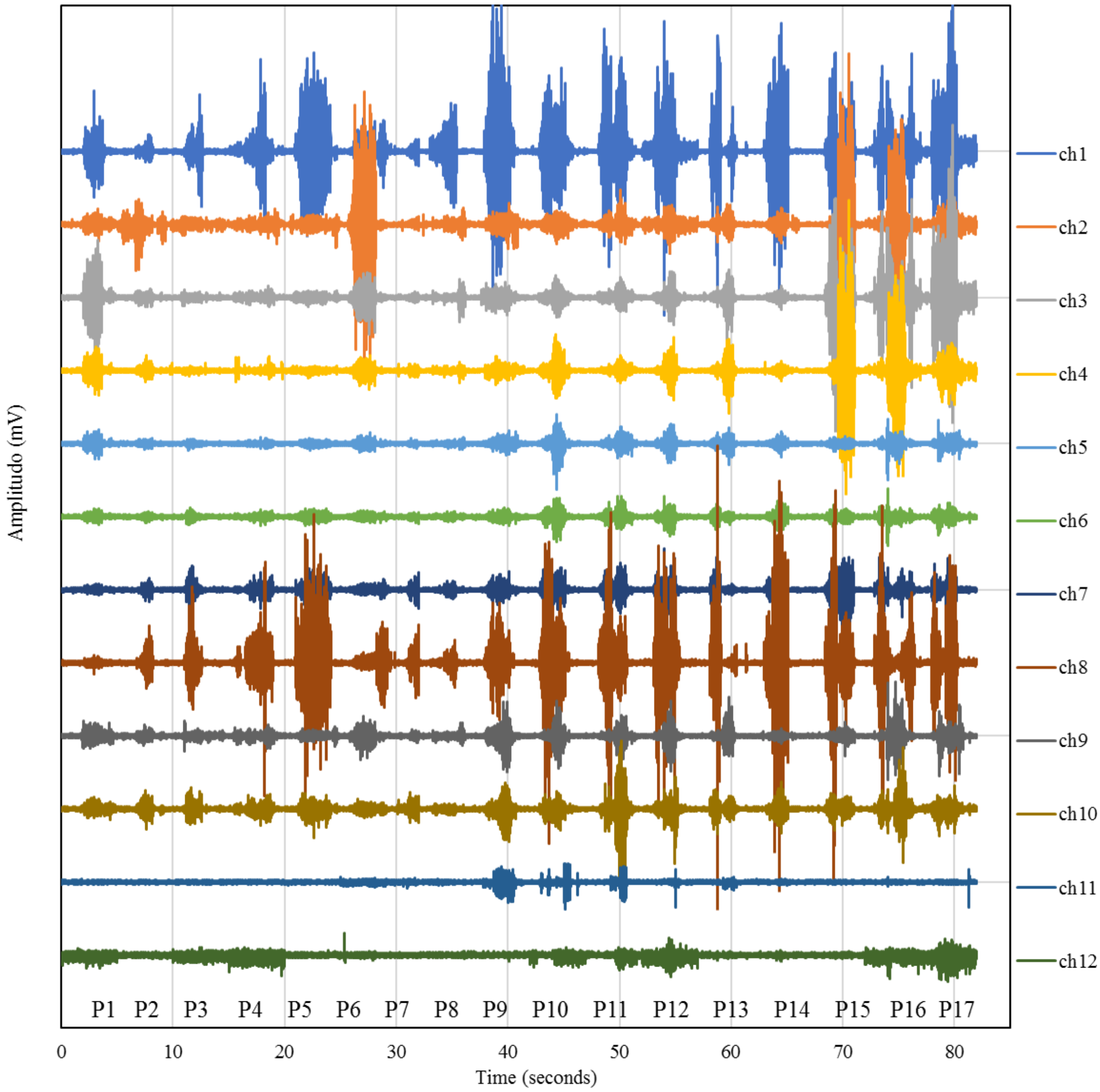


Figure 1. The representation of the EMG signal which is collected from the 12 of the channel from amputee from Ninapro DB3 database. The EMG signal is recorded while the amputees perform the 18-motion including the rest position.

2.2. *Experimental Setup*

In the data acquisition process, the EMG signal was recorded using a data acquisition card (NI-DAQ, PCMCIA 6024E, 12-bit resolution, National Instruments). The gain of the amplifier and frequency sampling was adjusted at 14,000 and 2,000 Hz, respectively. In the experimental stage, the amputee learned the eighteen motion by watching the hand motion on the monitor. Each motion was repeated for six-time which is consisted of (1) thumb up, (2) extension of index and middle (flexion on the others), (3) flexion of ring and little finger, (4) thumb opposing based of little finger, (5) abduction of all fingers, (6) finger flexed together in fist, (7) pointing index, (8) adduction of the extended finger, (9) wrist supination (axis middle finger), (10) wrist pronation (axis middle finger), (11) wrist supination (axis little finger), (12) wrist pronation (axis little finger), (13) wrist flexion, (14) wrist extension, (15) wrist radial deviation, (16) wrist ulnar deviation, (17) wrist extension with closed hand motion, and (18) rest. Each type of motion was assigned as P1 to P18 (including rest condition: P18). A representation of the EMG signal, from twelve channels, as shown in **Figure 1** which was generated from a subject when performed a sequential motion from motion P1 to P17. Between the motions, there was a rest condition for 3 seconds. Because of the EMG signal for channel 11 (biceps) and channel 12 (triceps) generated low and inconsistent activities to the hand motion so that in this work, the features extraction process was only performed for EMG signal from channel 1 to channel 10.

Furthermore, the EMG signal was extracted using six-time domain features which consist of root mean square (RMS), integrated EMG (IEMG), waveform length (WL), difference absolute standard deviation value (DASDV), Wilson amplitude (WAMP), and Myopulse percentage rate (MYOP) features. In order to discriminate the eighteen motions, the six-machine learning, which consists of Decision Tree, Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), K-Nearest Neighborhood (KNN) and Ensemble (a combination of machine learning), were used in this work. The effectiveness of this system was evaluated by varying the number of channel and feature used in the machine learning. The experimental setup and the classification system were shown in **Figure 2**.

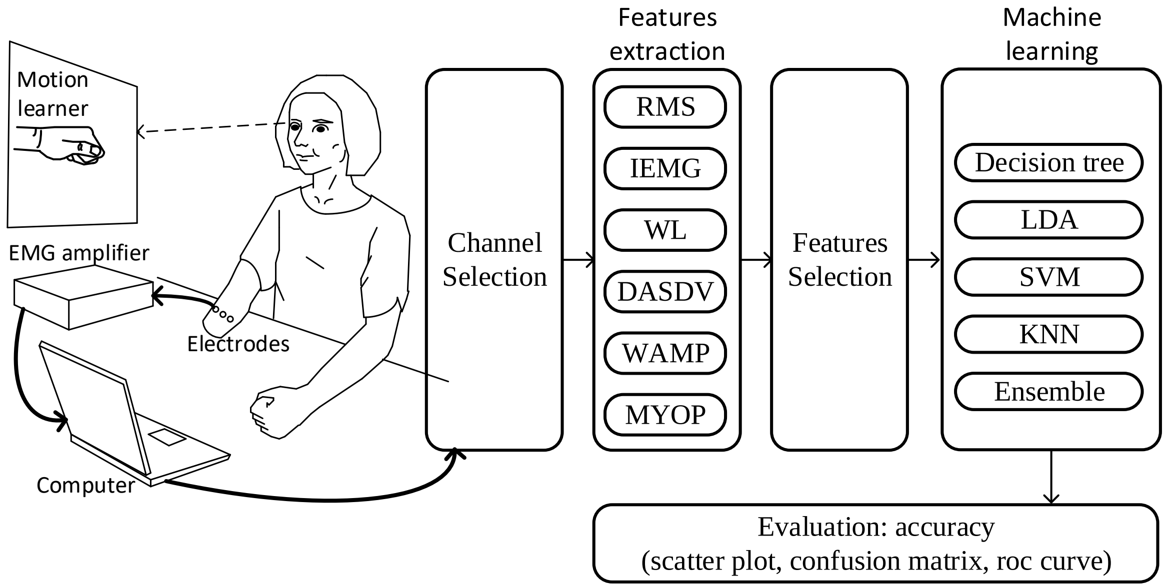


Figure 2. The experimental setup and the classification of the hand motion using machine learning.

2.3. Feature Extraction

The time domain feature was used in this study to extract the EMG signal which is related to the type of hand motion. The time domain feature was selected because the computation time is faster than other domains. A representation of the time domain feature was selected which is based on energy (RMS and IEMG), complexities (WL and DASDV), and frequency (WAMP and MYOP). Every EMG signal was extracted with a window length of 400 samples. So that, if the sampling frequency is 2,000 Hz (0.0005 seconds) then the window length in time is 0.2 seconds. In this study, the record of the EMG signal from 5 subjects consists of 5 (subjects) x 176k (raw EMG) x 12 (channel) records. Ten from twelve channels of EMG signal were extracted sequentially. Two channels (biceps and triceps) of the dataset were abandoned because those channels have a lesser response than others. The six time-domain features were written as follow (**Table 1**) [11]:

Table 1. The six-time domain features

(1) $RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	(2) $IEMG = \sum_{i=1}^{N} \lvert x_i \rvert$
(3) $WL = \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$	(4) $DASDV = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (x_{i+1} - x_i)^2}$
(5) $WAMP = \sum_{i=1}^{N-1} [f(\lvert x_i - x_{i+1} \rvert)]$ $f(x) = \begin{cases} 1, if \rightarrow x \geq threshold \\ 0, otherwise \end{cases}$	(6) $MYOP = \frac{1}{N}\sum_{i=1}^{N} [f(x_i)]$ $f(x) = \begin{cases} 1, if \rightarrow x \geq threshold \\ 0, otherwise \end{cases}$

where x is the EMG signal, N is the window length, and a threshold is a pre-defined constant

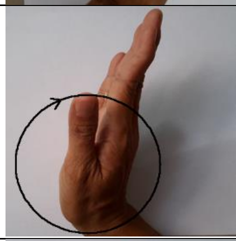
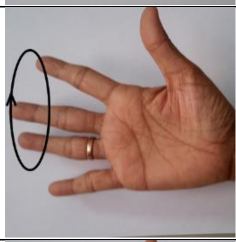
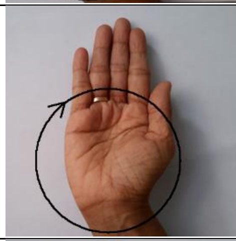
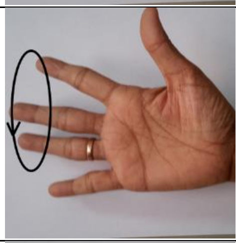
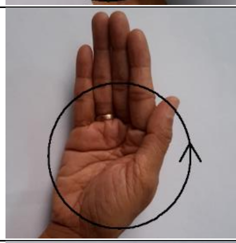
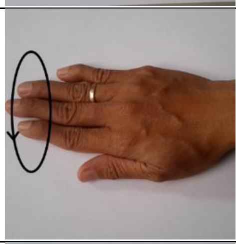
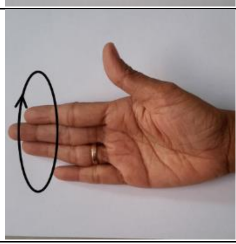
2.4. Machine Learning

The twenty-two classifier machines were chosen in this study to discriminate the eighteen hand motions. The type of hand motion shown on the monitor computer was indicated in **Table 2**. This motion is a standard type to be implemented on the prosthetics hand.

In this work, the 22 supervised machine learning was evaluated to classify the 18 classes of the hand motion, which are Decision Tree (DT), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), K-Nearest Neighborhood (KNN), and Ensemble. However, because of the EMG features have a linear and non-linear characteristic, then we explored the machine learning with various optimization and kernel. In the Decision Tree, the maximum number of splits was varied as four (Fine), twenty (Medium), and 100 (Coarse). For Discriminant Analysis machine learning, we used the linear and quadratics function. The various kernel of the SVM was also explored such as the linear, quadratic kernel, cubic kernel, fine Gaussian kernel, medium Gaussian, coarse Gaussian. In the supervised machine learning based on KNN, we also used some variation of the number of the neighborhood (NN). In the Euclidean matrix, the NN was set to 1, 10, and 100 for fine KNN, medium KNN, and coarse KNN, respectively. For cosine, cubic, and weighted KNN, the NN was set to 10 and distance matric was based on cosine, cubic, and weight, respectively. Ensemble machine learning is a combination of some machine learning which solves the same problem. In this study, the Ensemble machine learning consists of Boosted Tree, Bagged Tree, Subspace Discriminant, Subspace KNN, and RUSBoosted Tree [19].

Before the pattern recognition stage, the EMG signal (10 channels) was extracted using the six-time domain features (RMS, IEMG, WL, DASDV, MYOP, and WAMP). thus, after the feature extraction process, each record of the dataset, we have 60 features (which consist of 6 features and 10 channels) and 1 label. The number of labels to indicate the motion is 18 motions (consist of (1) thumb up, (2) extension of index and middle (flexion on the others), (3) flexion of ring and little finger, (4) thumb opposing based of little finger, (5) abduction of all fingers, (6) finger flexed together in fist, (7) pointing index, (8) adduction of the extended finger, (9) wrist supination (axis middle finger), (10) wrist pronation (axis middle finger), (11) wrist supination (axis little finger), (12) wrist pronation (axis little finger), (13) wrist flexion, (14) wrist extension, (15) wrist radial deviation, (16) wrist ulnar deviation, (17) wrist extension with closed hand motion, and (18) rest). We performed a pre-processing dataset using Microsoft Excel (Version 2016, Microsoft Corporation, USA) before it was used as input of the classifier machines. In this study, the Classification Learner from MATLAB (Version R2017b, Math Works, Inc., USA) was used to perform supervised machine learning. In the Classification Learner, a number of features and PCA (principal component analysis) was selected using feature selection menu. A number of training and testing dataset was set to 70% and 30%, respectively. For validation, a 5 k-fold was used to prevent the overfitting in the training stage. The accuracy of machine learning was shown using a confusion matrix and ROC curve.

Table 2. The eighteen hand motions have to be followed by amputee on the screen monitor (rest included) [15]

No.	Hand motion	No.	Hand motion	No.	Hand motion
1.		7		13.	
2.		8		14.	
3.		9		15.	
4.		10		16.	
5.		11		17.	
6.		12		18.	**REST**

In order to know the effective number of features and number of channels to discriminate the hand motion in the classifier machines, we performed a feature selection which is able to choose the number of features (2, 4, and 6 features) and channel selection (2, 4, 6, 8, and 10 channels). The accuracy for each number of features from all the subjects was recorded and analyzed using ANOVA or T-test for the significant difference of the accuracy between a number of features and number of channels. For statistic analysis, we used Microsoft Excel 2016 Profesional (Microsoft Corporation 2016, USA.) and an add-on library from Realstats (http://www.realstats.com).

3. Result and Discussion

The EMG signal shows a different pattern for each channel and the type of hand motion as shown in **Figure 1**. When the amputee performed the motion, channel 1 to 4 shows higher activities than others.

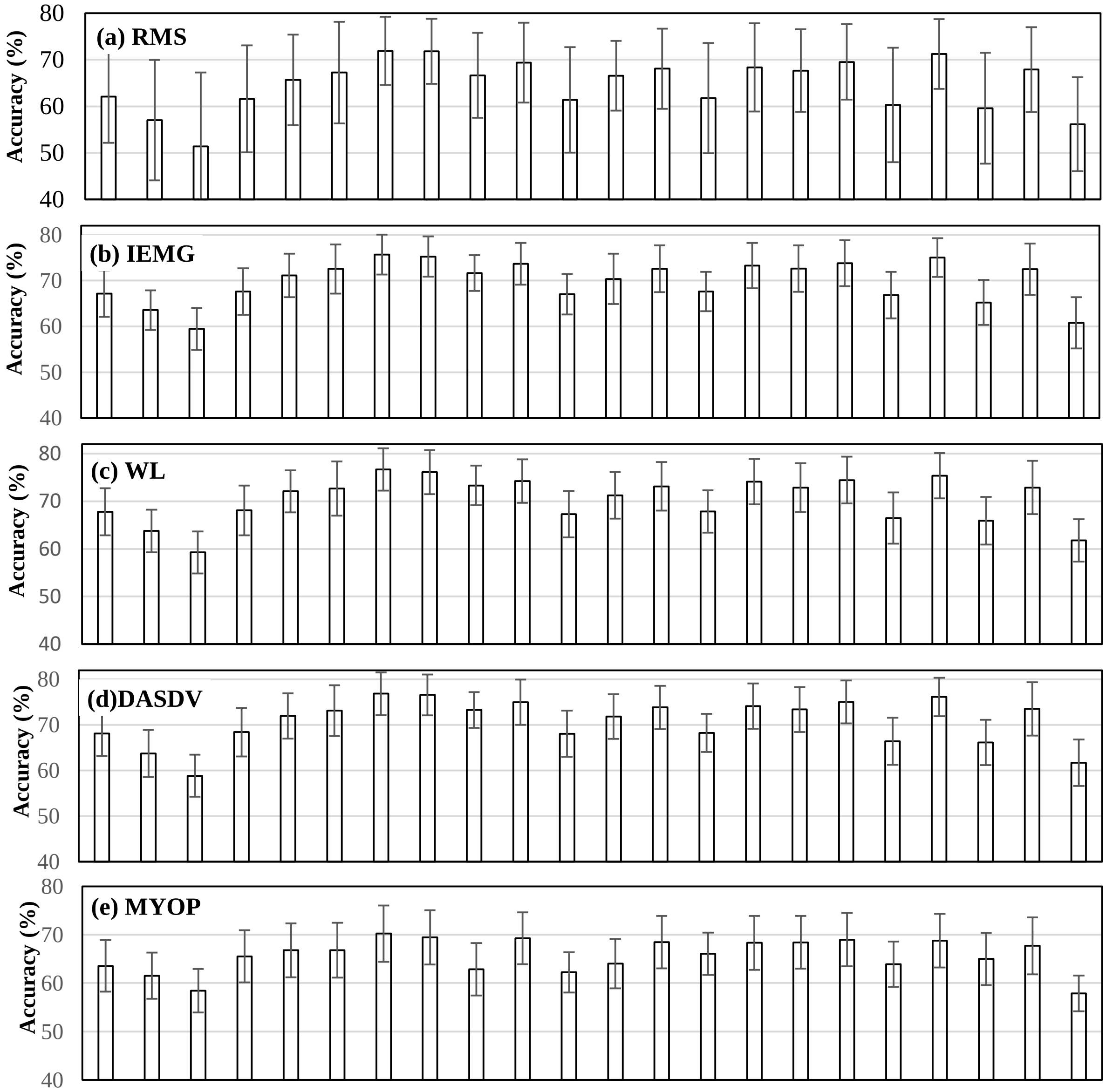


Figure 3. The accuracy of the machine learning in discrimination of 18 motion based on six-time domain feature (a) RMS, (b) iEMG, (c) WL, (d) DASDV, (e) MYOP, and (f) WAMP.

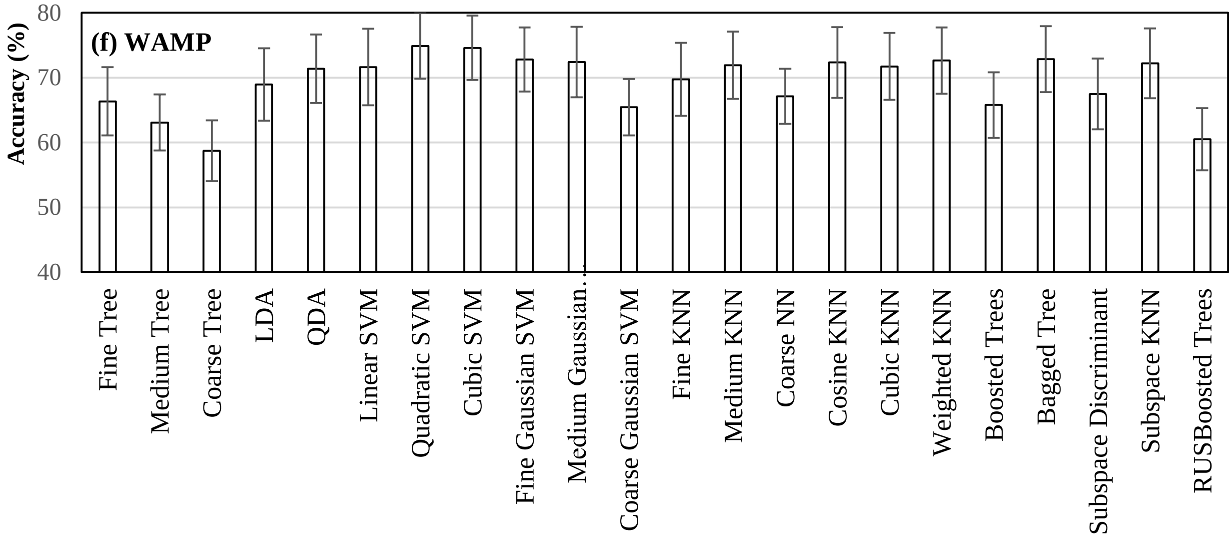


Figure 3. (Continued)

True class

	P1	P10	P11	P12	P13	P14	P15	P16	P17	P2	P3	P4	P5	P6	P7	P8	P9	R
P1	79	0	0	2	0	0	0	1	1	0	0	0	0	0	0	6	3	1
P10	0	90	7	5	2	0	0	2	0	0	0	0	0	0	0	0	0	1
P11	0	0	63	11	2	2	3	4	1	0	0	5	5	3	0	2	2	1
P12	0	6	7	63	4	2	0	2	4	0	2	7	1	1	0	2	2	1
P13	2	4	3	0	59	11	5	8	1	0	0	4	0	12	0	0	0	1
P14	0	0	3	6	11	64	2	2	1	0	0	3	1	5	0	0	0	1
P15	0	0	0	0	2	13	80	2	0	0	0	0	1	6	0	0	2	1
P16	2	0	0	3	7	4	7	59	11	0	4	1	4	5	0	0	2	1
P17	2	0	0	2	5	4	2	12	73	17	0	0	0	2	0	0	1	1
P2	0	0	0	0	0	0	0	0	0	72	17	0	0	0	2	0	0	1
P3	6	0	0	0	0	0	0	1	0	21	70	4	0	0	4	4	0	1
P4	0	0	2	2	2	0	0	0	1	0	6	66	4	1	0	0	0	1
P5	0	0	2	0	4	0	0	5	1	0	0	5	72	3	0	0	0	1
P6	2	0	0	0	2	0	2	1	0	0	0	1	3	62	0	0	1	1
P7	0	0	0	0	0	0	0	0	0	2	0	0	0	0	91	0	0	1
P8	3	0	3	3	0	0	0	2	0	0	0	1	0	0	0	84	0	1
P9	6	0	5	2	0	0	0	0	5	0	0	0	0	0	0	2	85	1
R	0	0	3	2	2	0	0	1	0	5	0	0	1	3	4	0	2	85

Predicted class

Figure 4. The confusion matrices for quadratic SVM using WL feature. The accuracy is in % unit. The diagonal matrices which assigned with green color show training and testing with the same pattern. (R is rest condition)

Each EMG signal generated from channels was segmented for windows length of 400 samples and extracted using the six-time domain features. Twenty-two machine learning was explored in this study to obtain the fit model and highest performance in classifying the hand motion. The hand motion from all subjects was trained and tested with a proportion of 70 % and 30 %, respectively. Each training and testing of machine learning was performed based on the EMG features (RMS, IEMG, WL, DASDV, MYOP, and WAMP). **Figure 3** shows that machine learning is able to discriminate 18 motions (including rest condition) based on 22 machine learning as shown in Figure 3 but with different accuracy. The top of the bar chart indicated the average accuracy of the machine learning and followed by the standard deviation of the accuracy.

After the exploration (training and testing), it was proven that a quadratic SVM have the best accuracy in the classification of the eighteen hand motions. The average accuracy (from all subjects) based on the quadratic SVM for RMS, IEMG, WL, DASDV, MYOP and WAMP features were 71.9±7.31%, 75.7±4.36%, 76.68±4.42%, 76.68±4.65%, 70.22±5.81%, and 74.88±5.02%, respectively. The statistics show that the WL features have the best accuracy in classifying the 18 hand motions. Among other kernels (linear, cubic, fine, medium, and coarse Gaussian), the SVM with the quadratic kernel showed the best accuracy. This is because the EMG characteristic have a non-linear response to the hand motion and the quadratic is the fittest model in the SVM classifier. The cubic kernel was also fit to be used on the SVM model due to the characteristic of the EMG signal as approached to the cubical. On the other hand, the accuracy of the machine learning based on coarse Decision Tree showed the worst classifier in classifying the 18-hand motions. The accuracy of the coarse Decision Tree with RMS feature was 51.4±15.90%.

In this work, our finding proved that the SVM based on quadratic kernel was superior to the other machine learning. A representation of a confusion matrices which was calculated based on SVM (quadratic kernel) was shown in **Figure 4**. The accuracy on the confusion matrices was resulted based on WL feature. Each type of hand motion showed a different accuracy. In the matrices, the hand motion of P7 shows higher accuracy (91%) than the others. The lowest accuracy was founded at hand motion of P6 (62%). In the matrices, the misclassification was founded on hand motion of P2 (72%) which is influenced by hand motion of P3 (21%) and P17 (17%). This problem is reasonable because of the P2, P3 and P17 related to the same EMG activities (as shown in **Figure 1**).

The effectiveness of the number of muscles in machine learning was investigated in this study. In this investigation, we selected the SVM with the quadratic kernel as proven to be the best machine learning to classify the 18-hand motions. The highest accuracy of the SVM (quadratic kernel) for ten channels is 76.68±4.42% (mean ± standard deviation). The waveform length (WL) feature was also selected due to the higher accuracy than the others. In the investigation, we reduced the number of muscles (channels) then each number of muscles, we calculated the accuracy of the machine learning. The accuracy of the SVM (quadratic kernel) for the various number of channels is shown in **Figure 5.** It was proved that the accuracy of machine learning was influenced by the number of channels. The bar chart shows the mean value of the accuracy (from all subjects) and the error bar shows the standard deviation of the accuracy. The statistics show that there is a high relationship between the number of channels and accuracy (0.98). It means that the smaller number of channels will reduce the accuracy of machine learning. For a statistics test, all of the accuracy data from all channels (from all the subjects) were pooled and statistical ANOVA single factor was performed. The statistics show that the p-value is higher than 0.05 (p-value=0.257 and F=1.355). It means that there was no significant difference of accuracy among the number of channels. This finding shows that the machine learning was able to classify 18 hand motions (including rest condition) with 3 channels with no significant difference of accuracy if we compared to the machine learning with 9 channels (p-value>0.05). In this investigation, the minimum number of channels which are able to classify the 18-hand motions was 3 channels. When we tried the number of channels was 2, the machine learning was not able to train the model because of the number of the class was too many (18 class or hand motion). This result proved that the minimum number of channels which can be used to discriminate the 18 types of hand motion was 3 channels.

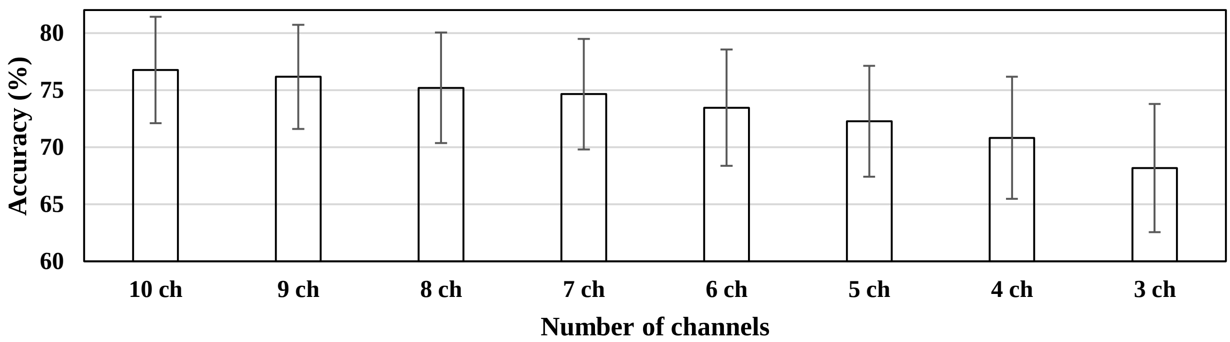


Figure 5. The accuracy of the machine learning based on a number of channels. The accuracy was calculated using quadratic SVM and WL feature.

As a comparison of this study, previous works also used this dataset (Ninapro, DB3) to investigate the hand motion from an amputee person. At the point of view of the machine learning, Atzori et. al. also founded that the SVM has better accuracy (45.19±14.75%) to discriminate the 18 hand motions than other machine learning (Random Forest and K-NN) [15] [20]. Al-timemy et. al. investigated a classifier to discriminate 6 motions (class) with 3 different forces (low, medium and high). They found the accuracy was 93%, 90.3%, and 82% for low, medium, and high force, respectively [21]. Even though the accuracy of the Al-timemy's work was better, but they used only 6 classes in their training and testing. Here, we can conclude that the number of class affects the accuracy of machine learning. The quality of the EMG signal was affected by many parameters such as 50 Hz noise from line power, noise artifact from hand motion, electrode position, sweat, and muscle fatigue. Muscle fatigue is a parameter which needs to be considered when we use the EMG signal as a control signal because the muscle fatigue could influence the amplitude and frequency of the EMG signal [22]. Therefore, this condition should be considered due to it will affect the feature extraction results and the classifier decision. Thus, in the future study, those parameters are needed to be consider in order to maintain the accuracy of machine learning.

4. Conclusion

After the investigation of 22 machine learning in classifying 18 classes (hand motion), the results showed that the SVM with the non-linear kernel (quadratic and cubic) has the best accuracy. Each feature extraction shows different accuracy, however, waveform length (WL) feature showed better accuracy than the others. We have investigated the effect of the number of channels (from 10 to 3 channels) to the accuracy of the machine learning. Up to 3 channel, the machine learning still able to recognize the18 hand motions but with different accuracy. However, the statistics show that a number of channels did not influence the accuracy significantly (p-value >0.05. In the future works, we suggested using the results of this study (which consisted of the number of channels, the type of feature extraction, and the machine learning) so that an effective prosthetics hand based on EMG signal can be developed.

References

[1] Ziegler-graham K, MacKenzie E J, Ephraim PL and Brookmeyer R 2008 *Archives of Physical Medicine and Rehabilitation* **89** 422–429.
[2] Utomo B, Triwiyanto, Suhartini, Luthfiyah S., and Mudjiono U, 2018 *International Conference on Science and Applied Science (ICSAS)* (Indonesia : Solo / AIP Published Omline) vol. 2014 p. 020105-1 - 020105-8.
[3] Leonardis D. *et al.* 2015 *IEEE Trans. Haptics* **8** 140–151.
[4] Triwiyanto, Wahyunggoro O, Nugroho HA, and Herianto, 2016 *Proc. International Annual Engineering Seminar, InAES* (Indonesia : Yogyakarta/IEEE Xplore) p 176 - 181.

[5] Segil JL, Huddle SA, and Weir RF, 2016 *IEEE Trans. Neural Syst. Rehabil. Eng.* **4320** c.25(6):1-10.
[6] Geethanjali P, 2016 *Med. Devices Evid. Res.* **9** 247–255.
[7] Engeberg ED, 2013 *Biomed. Signal Process. Control*, **8** 6–15.
[8] Kyriakopoulos KJ, Artemiadis PK, 2007 *IEEE/ASME international conference on advanced intelligent mechatronics*,(Switzerland: Zurich/IEEE Xplore) pp. 1–6.
[9] Fleischer C and Hommel G, 2008 *IEEE Trans. Robot* **24** 872–882.
[10] De Luca CJ, 1997 *J. Appl. Biomech* **13** 135–163.
[11] Triwiyanto, Wahyunggoro O, Nugroho H A, and Herianto, 2017 *Adv. Electr. Electron. Eng.* **15**, 448–458.
[12] Phinyomark A, Phukpattaranont P, and Limsakul C, 2012 *Expert Syst. Appl.* **39**7420–7431.
[13] Fougner A L, Stavdahl Ø, and Kyberd P J, 2014 *J. Neuroeng. Rehabil.* 1–13.
[14] Khushaba R N, Takruri M, Valls J, and Kodagoda S, 2014 *Neural Networks* **55** 42–58.
[15] Atzori M, Gijsberts A, Castellini C, Caputo B, Hager A-G M, Elsig S, Giatsidis G, Bassetto F, & Müller H, 2014 *Sci. Data* **1** 1–13.
[16] Khushaba R N, Member S, Al-timemy A H, Al-ani A, and Al-jumaily A, 2017 *IEEE Trans. Neural Syst. Rehabil. Eng.* **25**, 1821 - 1831.
[17] Martini, 2012 *Fundamental of Anatomy and Physiology*, 9th ed. Boston: Pearson Education.
[18] Stegeman D. and Hermens H, 2007 *Línea. Dispon. en http//www. med. ...*, pp. 108–112.
[19] Gubta V, Bhavsar A, 2017 *International Conference on Computer Analysis of Images and Patterns* CAIP 2017 p. 354–366.
[20] Atzori M, Gijsberts A, Castellini C, Caputo B, Hager A-G M, Elsig S, Giatsidis G, Bassetto F, & Müller H 2016 *J. Rehabil. Res. Dev.* **53**, 345–358.
[21] Al-timemy A H, Khushaba R N, and Bugmann G, 2015 *IEEE Trans. Neural Syst. Rehabil. Eng.*, **4320** c.
[22] Triwiyanto, Wahyunggoro O, Nugroho H A, and Herianto H, 2018 *Comput. Electr. Eng.* **71** 284–293.