Turnitin Originality Report

Processed on: 2020年03月03日 09:48 WIB

ID: 1268121587 Word Count: 5348 Submitted: 1

Investigation of the Number of Features and Muscles for an Effective Hand Motion Classifier Using Electromyography Signal By M Ridho Ma'ruf Similarity Index

Similarity by Source

Internet Sources: 10% Publications: Student Papers:

10% 11%

14%

3% match (Internet from 05-Feb-2019)

https://research.aalto.fi/files/11454450/Vlasov 2016 J. Phys. Conf. Ser. 741 012183.pdf

3% match (student papers from 24-Mar-2018)

Submitted to Universiti Teknikal Malaysia Melaka on 2018-03-24

2% match (Internet from 23-Dec-2019)

http://eprints.unm.ac.id/16202/18/Analysis%20of%20phenolic%20content%20and%20antioxidant%20activity%20of%20cocoa%20phod%20husk

1% match (Internet from 19-Mar-2019)

https://manorprimary.com/usr/docs/2017/Ofsted%202016%20RAISE%20Online%20Summary%20Report.pdf

1% match (publications)

Triwiyanto, O Wahyunggoro, H A Nugroho, Herianto. "Performance Analysis of the Windowing Technique on Elbow Joint Angle Estimation Using Electromyography Signal", Journal of Physics: Conference Series, 2018

1% match (student papers from 13-May-2019)

Submitted to University of Ulster on 2019-05-13

1% match (publications)

HAMIDREZA NAMAZI. "DECODING OF HAND GESTURES BY FRACTAL ANALYSIS OF ELECTROMYOGRAPHY (EMG) SIGNAL", Fractals, 2019

1% match (publications)

Triwiyanto, Oyas Wahyunggoro, Hanung Adi Nugroho, Herianto. "Upper Limb Elbow Joint Angle Estimation Based on Electromyography Using Artificial Neural Network", 2018 12th South East Asian Technical University Consortium (SEATUC), 2018

1% match (Internet from 04-Jan-2020)

http://sintadev.ristekdikti.go.id/authors/detail?id=5995873&view=overview

1% match (publications)

Khushmeen Kaur Brar, Ashima Kalra, Piyush Samant. "Automated textural features based skin disease diagnosis system", 2019 5th International Conference on Signal Processing, Computing and Control (ISPCC), 2019

1% match (Internet from 19-Nov-2019)

https://www.birpublications.org/doi/full/10.1259/bjr.20190286

< 1% match (publications)

Bong Siao Zheng, M Murugappan, Sazali Yaacob, Subbulakshmi Murugappan. "Human emotional stress analysis through time domain electromyogram features", 2013 IEEE Symposium on Industrial Electronics & Applications, 2013

< 1% match (student papers from 09-Jan-2020)

Submitted to Dokuz Eylul Universitesi on 2020-01-09

< 1% match (Internet from 13-Feb-2020)

 $\underline{\text{https://media.neliti.com/media/publications/294910-fetal-doppler-simulator-based-on-arduino-6837bcba.pdf}$

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 To cite this article: Triwiyanto Triwiyanto et al 2019 J. Phys.: Conf. Ser. 1373 012051 View the article online for updates and enhancements. This content was downloaded from IP address 114.125. 77.73 on 02/03/2020 at 14:53 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-ne 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 Content from this work may
be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must
maintain attribution to the author(s) and the title of the work, journal citation and DOI. Published under licence by IOP
Publishing Ltd 1 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 <u>Tree, Medium</u> Decision <u>Tree, Coarse</u> Decision <u>Tree, Linear Discriminant</u> Analysis, <u>Quadratic</u>
<u>Discriminant</u> Analysis, <u>Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian</u>
<u>SVM, Fine KNN, Medium KNN, Coarse KNN,</u> Cubic <u>KNN,</u> Weighed <u>KNN,</u> and <u>Ensemble</u> (such as: <u>boosted</u> tree, <u>bagged</u> 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. Features Machine extraction learning Motion learner RMS IEMG Decision tree EMG amplifier Channel WL
Features LDA Selection DASDV Selection SVM Electrodes WAMP KNN MYOP Ensemble Computer Evaluation: accuracy
(scatter plot, confusion matrix, roc curve) 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 N (1) RMS ? 1 N xi2 | xi | N i ?1 ? (2) IEMG ? ? \frac{!}{!}?1 N ?1 (3) WL ? ? \frac{!}{!}xi?1 ? xi | N \frac{?}{!}1 (4) DASDV ? N \frac{?}{!}2 i \frac{?}{!}1 (xi?1 ? xi) 2 1 \frac{!}{!}2 1 (5) N ?1 WAMP ? ?[ f (| xi ? xi? 1 |)] i \frac{?}{!}1 f (x) ? \frac{?}{!}?2 i, if ? x ?
threshold ??0, otherwise (6) MYOP ? N1 ?iN?1[ f(xi)] f(x)? ???1, if? x? threshold ??0, otherwise 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. 80 Accuracy (%) 70 (a) RMS 60 50 40
Accuracy (%) 80 (b) IEMG 70 60 50 40 Accuracy (%) 80 (c) WL 70 60 50 40 Accuracy (%) 80 (d)DASDV 70 60 50 40 80
Accuracy (%) (e) MYOP 70 60 50 40 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. Accuracy (%) 80 (f) WAMP 70 60
50 40 Medium Gaussian... Fine <u>Tree Medium Tree</u> Coarse <u>Tree</u> LDA QDA <u>Linear SVM Quadratic SVM Cubic SVM Fine</u>
Gaussian SVM Coarse Gaussian SVM Fine KNN Medium KNN Coarse NN Cosine KNN Cubic KNN Weighted KNN Boosted
Trees Bagged Tree <u>Subspace</u> Discriminant <u>Subspace KNN</u> RUSBoosted <u>Trees</u> Figure 3. (Continued) 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\ 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\ True\ class\ P16\ P17\ P2\ 2\ 2\ 0\ 0\ 0\ 0\ 0\ 0\ 3\ 2\ 0\ 7\ 5\ 0\ 4\ 4\ 0\ 7\ 2\ 0\ 59\ 12\ 0\ 11\ 73\ 0\ 0\ 17\ 72\ 4\ 0\ 17\ 1\ 0\ 0\ 4
0\ 0\ 5\ 2\ 0\ 0\ 0\ 2\ 0\ 0\ 0\ 2\ 1\ 0\ 1\ 1\ 1\ 1\ P3\ 6\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 2\ 1\ 70\ 4\ 0\ 0\ 4\ 4\ 0\ 1\ P4\ 0\ 0\ 2\ 2\ 2\ 0\ 0\ 0\ 1\ 0\ 6\ 6\ 4\ 1\ 0\ 0\ 0\ 1\ P5\ 0\ 0\ 2\ 0
00 2 000 1 000 84 0 1 P9 6 0 5 2 0000 5 000000 2 85 1 R 0 0 3 2 2 0 0 1 0 5 0 0 1 3 4 0 2 85 P1 P10 P11 P12
P13 P14 P15 P16 P17 P2 P3 P4 P5 P6 P7 P8 P9 R 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 (pvalue>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. 80 Accuracy (%) 75 70 65 60 10 ch 9 ch 8 ch 7 ch 6 ch 5 ch 4 ch 3 ch Number of 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 the 18 hand motions but with different accuracy. However, the statistics show that a number of channels did not influence the accuracy significantly (pvalue >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. 397420-7431. [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. The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 1/2 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/ 1373 /1/ 012051 The 2019 Conference on Fundamental and Applied Science for Advanced Technology Journal of Physics: Conference Series IOP Publishing 1373 (2019) 012051 doi:10.1088/1742-6596/1373/1/012051 2 3 4 5 6 7 8 9 10 11