
# INDEX FINGER MOTION RECOGNITION USING SELF-ADVISE SUPPORT VECTOR MACHINE

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***Abstract- Because of the functionality of an index finger, the disability of its motion in the modern age can decrease the person's quality of life. As a part of rehabilitation therapy, the recognition of the index finger motion for rehabilitation purposes should be done properly. This paper proposes a novel recognition system of the index finger motion suing a cutting-edge method and its improvements. The proposed system consists of combination of feature extraction method, a dimensionality reduction and well-known classifier, Support Vector Machine (SVM). An improvement of SVM, Self-advise SVM (SA-SVM), is tested to evaluate and compare its performance with the original one. The experimental result shows that SA-SVM improves the classification performance by on average 0.63 %.***

**Index terms: Support Vector Machine, Self-advise SVM, pattern recognition.**

# I. INTRODUCTION

In the modern age, the index finger is a key limb in performing the complex and intricate tasks such as a tapping tablet and Smart phone, and many other activities. The disability in the index finger functionality will decrease the person's quality of life. Such disabilities can be resulted in either the loss of a limb, weakens the muscles or the limb impairment that, inevitably, the motor function recovery must be taken into action through the rehabilitation.

The efficacy of the rehabilitation therapy can be achieved optimally if the therapy is performed based on the user intention detected beforehand. The user intention detection beforehand promises the system with no or less processing delay, so that can enhance the user's comfort in performing the therapy. The intention can be obtained by recognizing electrical signals from the user's muscle activities in the forearm using Surface Electromyography signal (sEMG). The processing of the sEMG to detect the user's intention in advance can be done by using a pattern recognition method.

The EMG based pattern recognition consists of some steps which should be done in order. The first step is a filtering of EMG signal to remove a noise that possibly may degrade the recognition system performance. After filtering, a feature set is extracted from EMG signals using Time Domain and Frequency Domain Extraction method. Normally, the extracted features contain high dimension features so that the dimensionality reduction should be applied. Finally, the classification method is applied to recognize and detect the finger movement which is intended by the user. The effective feature extraction [1] and the classification method greatly determine the pattern recognition performance [2].

The combination of an effective feature extraction and classification method for a limb movement recognition which can be used as a reference or a control source for the Myoelectric Control System (MCS) started to be effective with the work of Hudgin et al [3]. Employing five time-domain features extracted from single EMG channel in the transient state and a multilayer perceptron (MLP), they were able to achieve an averaged classification accuracy of 91.25 % on nine limbed subjects and 85.5 % on six amputee subjects. On the other hand, because the MLP needs the heuristic specification of its architecture and the training algorithm, LDA classifier accompanied by the frequency domain features were utilized by Englehart et al [4, 5]. They succeeded to recognize the hand movement with an accuracy of 92%. Up to now, different EMG-based classification have been used in the limb movement recognition such as k-Nearest Neighbor (kNN) [6] [7], Neuro-Fuzzy [8], and Support Vector Machine (SVM) [9].

Nowadays, SVM has been used frequently in the various classification problems, including the pattern-recognition-based MCS [9-11] due to its generalization performance in the classification cases over other aforementioned methods. Some improvements on SVM have been proposed like Self-advise SVM (SA-SAVM) [12]. SA-SAVM tries to get benefit from the knowledge that is acquired from the training phase, and transfer it to the testing phase. This transferred knowledge is obtained from the misclassified data of the training phase. This paper proposes a recognition system which employs Self-Advise SVM (SA-SVM) for classifying the index finger motions. Time domain features which are extracted from sEMG signals are reduced its dimensionality using Spectral Regression Discriminant Analysis (SRDA) [13], an extension of LDA, before being classified by SA-SVM.

The paper was organized as follows. A basic concept of SVM, SA-SVM and SRDA is presented in section II. Section II also provides the proposed recognition system and the experimental procedures for the data acquisition. Section III describes the experimental results, and statistical analysis of the proposed system with respect to the classification accuracy. Finally, section IV provides the conclusion.

## II. METHODS

### a. Proposed method

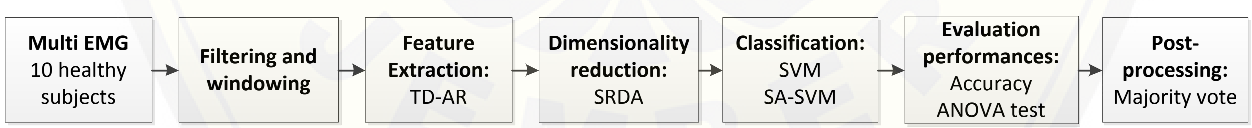



Figure 1. Pattern recognition method for the finger motion classification

The proposed recognition system consists of some steps as described in Figure 1. First step is the EMG acquisition using a data acquisition device. The filtering and windowing are applied to the acquired data before being extracted using a time domain (TD) and an autoregressive (AR) feature set. SDRA is utilized to reduce the dimension of the features. Then, the reduced data were classified using SA-SVM which was compared with the original SVM and refined by using the majority vote.

b. Experimental procedures

The EMG signals used in this paper were obtained from [10]. EMG signals of ten normal people aged 21-35 years (six males and four females) were recorded. This work only used one channel surface EMG. An electrode pair of the self-adhesive Ag–AgCl electrodes (Tyco healthcare, Germany) was placed on the forearm to capture muscle activities from Flexor Digitorum superficialis (FDS) muscle. A custom-built multi-channels amplifier with 1000 gain was used to record the data. Data were sampled at a rate of 2000 MHz with 16 resolution using USB-6210 data acquisition device from national instruments.

In recording the data, the subject performed two actions, a rest and flexion of index finger while sitting on a chair and watching the signal recorded in real-time. Six trials were recorded for each movement with a rest time 5 second between trials. This work only considered the signal in steady state and removes the transient state.

The collected EMG signals were processed in the Matlab 2012b installed in the Intel Core i5 3.1 GHz desktop computer with 4 GB RAM running on Windows 7 operating system. The signals were filtered digitally by a band pass filter between 20 and 500 Hz with a notch filter to remove the 50 Hz line interference. Finally, the EMG signals were down sampled to 1000 Hz. Two classes of index finger motions were considered, Flexion (F) and Rest (R). The data collected were divided into training data and test data by using a 4-fold cross validation.

c. Feature Extraction

The features extracted from a time domain feature set consist of Waveform Length (WL), Slope Sign Changes (SSC), Number of Zero Crossings (ZCC), and Sample Skewness (SS). In addition, some parameters from Hjorth Time Domain Parameters (HTD) and Auto Regressive (AR) Model Parameters were included. The AR model parameters have been proven to be stable and robust to the electrode location shift and the change of signal level [14]. The all features were concatenated and reduced using SRDA [13]. SRDA is an extension of LDA which can deal with a singularity and a large data set.

d. Support Vector Machine (SVM)

SVM is a classifier which decides a hyperplane to separate two class data optimally. Suppose there are empirical separable data $\{x_i,y_i\}$ where $x_i \in R^N$ is an N dimensional space and the associated $y_i \in \{-1,1\}$. The solution of SVM is formulated in such a way to obtain a quadratic programming (QP) problem which is unique and global. The hyperplane that can divide the data into two classes is:

$$w \times \phi(x) + b = 0 \quad w \in R^N, \quad b \in R \tag{1}$$

The QP problem can be used to obtain optimal hyperplane with maximum-margin and bounded error on the training data as follows:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i \tag{2}$$

$$y_i(w \times \phi(x_i) + b) \geq 1 - \xi_i, \quad i = 1,\ldots,m \tag{3}$$

The equation (2) gives a maximum margin of separation between classes while equation (3) provides an upper bound for the error. The solution for equation (2) can be done via its Lagrange function. By considering kernel $k(x_i,x_j) = \phi(x_i).\ \phi(x_j)$ , the Lagrange function will be:

$$\max_{\alpha} \sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{m}\alpha_i\alpha_j y_i y_j k(x_i,x_j) \tag{4}$$

$$w = \sum_{i=1}^{m} y_i\alpha_i\phi(x_i), \sum_{i=1}^{m}\alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C \quad \forall i \tag{5}$$

The equation (5) shows the optimal hyperplane as the linear combination of the training samples with $\alpha_i$ not zero. The classifier can be constructed from these samples which are known as support vectors. Finally the output of SVM using a kernel function is:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{m} y_i\alpha_i k(x,x_i) + b\right) \tag{6}$$

Different kernels can be selected in SVM:

Linear kernel : $K(x_i,x_j) = x_i x_j$

Polynomial kernel : $K(x_i,x_j) = (\gamma x_i x_j + q)^d$

Radial Basis Kernel : $K(x_i,x_j) = \exp(-\gamma\|x_i - x_j\|^2)$

Sigmoid kernel : $K(x_i,x_j) = \tanh(\gamma x_i x_j + q)$

Here q,d,γ are the kernel parameters which are more than zero.

e. Self-Advise SVM

Self-advise SVM extracts knowledge from misclassified data in the training phase to be considered in the testing phase. The knowledge is acquired by generating advice weights based on the use of the misclassified training data. These weights eliminate the misclassified data in testing phase [12].

The misclassified data set in training stage can be defined as:

$$MD = \bigcup_{i=1}^{N} x_i \mid y_i \neq \operatorname{sgn}\left(\sum_{j=1}^{m} y_j \alpha_j k(x_i, x_j) + b\right) \tag{7}$$

Then, the neighbourhood length of each $x_i$ of MD is calculated by using the following equation:

$$NL(x_i) = \min_{x_j}\left(\|x_i - x_j\| \mid y_i \neq y_j\right)/2 \tag{8}$$

where $x_j$, j=1,.., N are the training data which do not belong to the MD set. For a higher dimension mapping, the distance between $x_i$ and $x_j$ can be calculated using:

$$\|\theta(x_i) - \theta(x_j)\| = \left(k(x_i, x_i) + k(x_j, x_j) - 2k(x_i, x_j)\right)^{0.5} \tag{9}$$

Based on the NL, the advised weight of each $x_k$ from the test set $AW(x_k,j)$ can be computed as follows:

$$AW(x_k, j) = \begin{cases} 0, & \forall xi \in MD,\ \|x_k - x_i\| > NL(x_i)\ or\ MD = NUL \\ \sum \frac{|h(x_i)|}{1 + \|x_k - x_i\|^2}, & \exists xi \in MD,\ \|x_k - x_i\| \leq NL(x_i)\ or\ y_i = J \end{cases} \tag{10}$$

The AWs describe the closeness the test data and the misclassified data.

f. Simulation environment

The pattern recognition of the index finger motion were processed on the Matlab 2012b running on Windows 7 operating system. Time-domain and frequency domain feature were extracted using myoelectric toolbox [15] and Biosig toolbox [16]. In addition, all experiments in this paper were done using LIBSVM, a free SVM code from [17]..

## III. RESULT AND DISCUSSION

a. Window length experiment

Before we tested the performance of SA-SVM compared to SVM, some experiments were done to find out the best composition of the recognition system for the index finger motions. The first experiment was a window length selection. There are two windowing methods that can be used to divide the signals into several segments in which the recognition system is done on each segment. Both are the disjoint and overlapping windowing [9, 18]. The disjoint windowing is only associated with the window length while the overlapped window is associated with the window length and window increment. The window increment is a time interval between two consecutive windows. In general, the disjoint windowing is the overlapped windowing in condition the window increment is equal to the window length.

In this experiment, the window length varies from 50 to 500 ms with a fixed window increment of 50 ms. All were done and verified using 4-fold cross validation. The recognition system will utilize the disjoint windowing when the window length is 50 ms because it has same long as the window increments. The result of the window length experiment is presented in figure 2. The figure indicates that all window lengths achieve a good accuracy except the 50 ms-window. Thus, 100 ms or more windows could be chosen as a candidate window length for next experiments. Finally, the 150 ms-window length was selected as the optimum window length along with a 50 ms-window increment by considering the smallest accuracy deviation and the shortest window length.

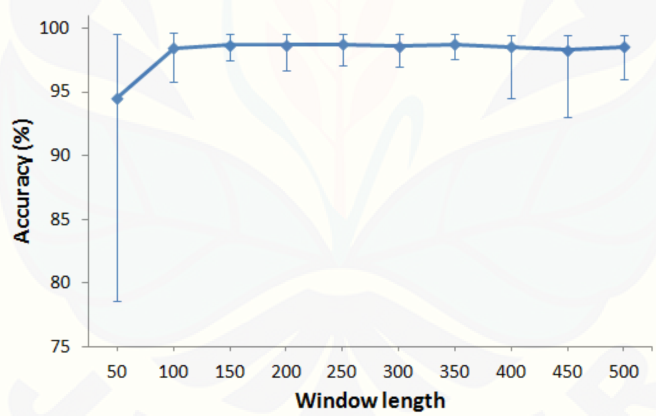
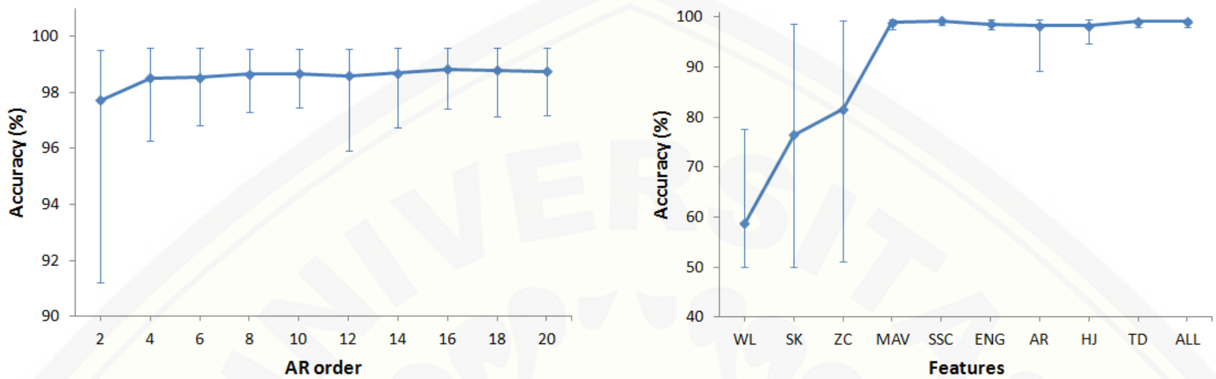



Figure 2. The average accuracy over 10 subjects across different window lengths

b. Feature selection test

The next experiment was the feature selection that is used to investigate the best possible feature for the recognition system. Several individual time-domain features, an autoregressive (AR) feature, a time domain feature set from [18] and all feature combination were tested and verified using the 4-fold cross validation. The results are shown in figure 3. Figure 3a shows that the higher order of AR does not always perform a good accuracy. Based on the accuracy and the accuracy deviation, we selected the AR order of 10 as the optimum order for the proposed system. Different from the figure 3a, the figure 3b describes the accuracy of an individual feature set and combined feature set. MAV, SSC, and all-feature combination are the most robust feature set amongst others. For the next experiment, this work extracted the features from all methods and combined them into one feature set.




(a) (b)

Figure 3. The average accuracy of 10 subjects of feature selection experiments (a) an Autoregressive experiment (b) various feature extraction method (Waveform Length (WL), Slope Sign Changes (SSC), Number of Zero Crossings (ZCC), and Sample Skewness (SS), Hjorth Time Domain Parameters (HTD) and Auto Regressive parameter (AR), Engelhart feature set [18] )

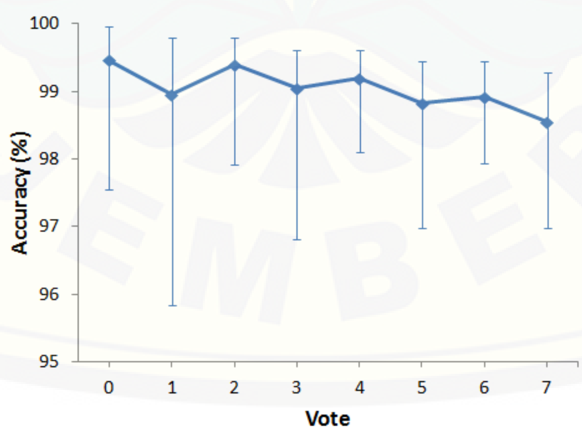



Figure 4. The average accuracy of 10 subjects with different number of votes

c. The majority vote test

After determining the window length and the feature extraction method, we performed another experiment to decide the number of votes that should be selected in the proposed system. It is shown in Figure 4 that the vote 0 gives the best accuracy compared to other votes. Another lesson taken from this result is a high number of votes not always perform better accuracy than a small vote numbers.

d. Classification performance (comparison SVM and SA-SVM)

The previous experiments result in an optimum system that could be used to evaluate the performance of SA-SVM in enhancing the original SVM in classifying the index finger movement. This system will be tested using four different kernels, linear, radial basis function (RBF), polynomial, and sigmoid kernel. Each of them will be presented separately and then compared to each other. A 4-fold cross validation is implemented to all experiments. The grid search method is utilized to find out the best parameters for SVM in different kernels.

The linear kernel is discussed first and the result is depicted in the figure 5 (left). Amongst ten subjects tested, SA-SVM can improve the accuracy on subject 3 and 5. In these two subjects, the improvement is significant as shown by p-value $< 0.05$. These p-values were produced from a pairwise t-test of comparison between the original SVM and SA-SVM with a significance level set at 0.05. However, for other subjects, the classification accuracy between SVM and SA-SVM is not significantly different. Somehow, some improvements were achieved. Similar to the linear kernel, SA-SVM on the RBF kernel could enhance the classification accuracies but the improvement is statistically not significant as shown by the p-values in the figure 5 (right).

Besides two previous kernels, another two kernels, a polynomial and sigmoid kernel were also evaluated as can be seen in the figure 6 (left) and figure 6 (right) for the polynomial and sigmoid kernel, respectively. It is can be inferred that, on average, SA-SVM was able to advance the classification accuracy. However, the significant enhancement is obtained using the polynomial kernel on subject 3 and 5 only. Meanwhile, the performance of SVM and SA-SVM are similar on other subjects. Interestingly, there is no significant advancement in using the RBF and sigmoid kernel, but there is for another two kernels.

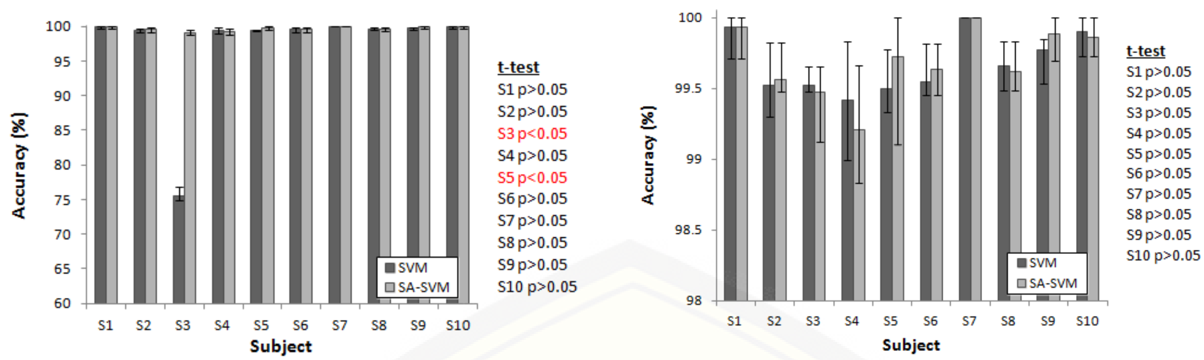



Figure 5. The Comparison of SVM and SA-SVM using the linear kernel (left) and RBF kernel (right)

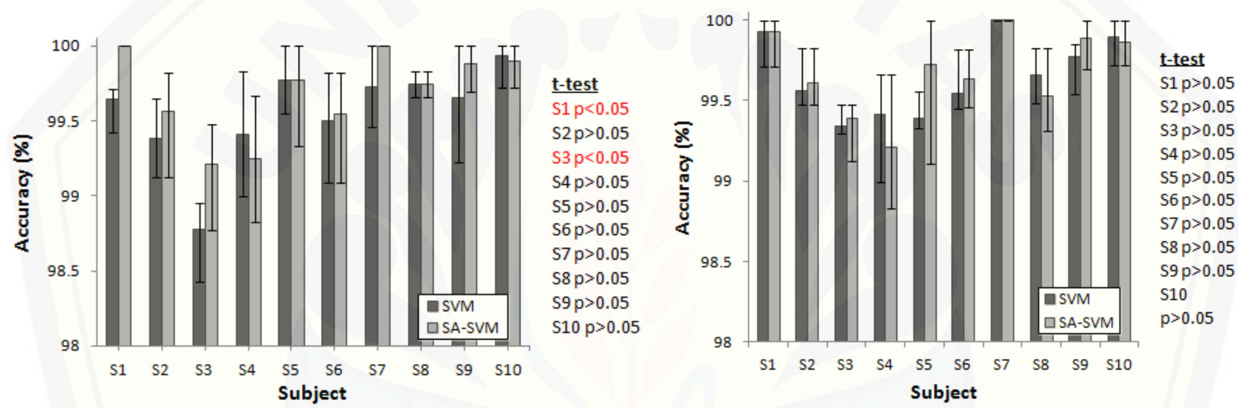



Figure 6. The Comparison of SVM and SA-SVM using the Polynomial kernel (left) and the Sigmoid kernel (right)

Table 1. The average accuracy over 10 subjects

| Kernel | SVM (%) | SA-SVM (%) | Improvement (%) |
|---|---|---|---|
| Linear | 97.2569 ±7.6125 | 99.6460±0.3170 | 2.3890 |
| Polynomial | 99.4620± 0.7230 | 99.5545±0.3222 | 0.0925 |
| RBF | 99.6740 ± 0.2091 | 99.684 ± 0.2421 | 0.0144 |
| Sigmoid | 99.6497 ± 0.2388 | 99.6754±0.2534 | 0.0258 |
| **Average** | **99.0107±2.1959** | **99.6411±0.2839** | 0.6304 |

In addition to discussion on individual subjects, the accuracy improvement in all subjects was also considered as well. As presented, in the Table 1, the average accuracy across 10 subjects shows that SA-SVM enhances the classification accuracy in all kernel types by on average 0.63 %. The enhancement of SA-SVM inevitably increases the processing time. As shown in Table 2, the processing time of SA-SVM is much longer than original SVM.

Table 2. The average processing time of each SVM over 10 subjects

| Kernel | SVM (s) | SA-SVM (s) |
|---|---|---|
| Linear | 0.011 ± 0.017 | 0.262 ± 0.213 |
| Polynomial | 0.026 ± 0.011 | 1.925 ± 5.378 |
| RBF | 0.033 ± 0.026 | 0.621 ± 0.477 |
| Sigmoid | 0.015 ± 0.009 | 0.204 ± 0.149 |

SA-SVM could enhance the classification performance of the original SVM. Its performance in recognizing the index finger motions is also presented as described in Figure 7. The figure shows that the SA-SVM recognized the index finger motion better than the rest condition in all kernels. Furthermore, in all kernels, the index fingers motion was able to be identified properly while the rest condition was not classified properly by all kernels especially the linear kernel. Nevertheless, the accuracy of the rest motion in all kernels was more than 90 %.

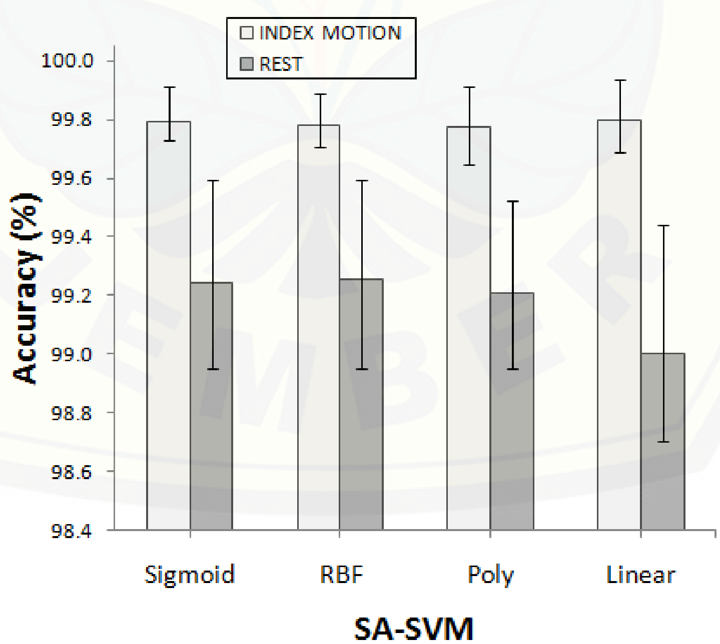



Figure 7. The SA-SVM performance in recognizing the index finger motion and the rest state across ten subjects using a four-fold cross validation

e. Future Development

The successfulness of this work can be implemented as a control source of an index finger exoskeleton which is intended to recover index finger functionality. It is mainly designated for a person who is paralysed on its index finger after stroke attack. The rehabilitation therapy is performed by assistance of the exoskeleton. Interestingly, by using the method presented here, the assistance given by the exoskeleton will be delivered based on the user intention. As a result, the person will feel the help given accordingly in a reasonable and convenient way.

In addition, the improvement of SA-SVM will be noticeable if the kernel parameters are determined properly using an optimization method instead of a traditional search-grid method. For that purpose, modified-PSO (Particle Swarm Optimization) proposed by Jatmiko et al [19] or artificial swarm optimization as explained in [20] could be used to search the best kernel parameters before being improved using SA-SVM.

## IV. CONCLUSION

This paper proposed a novel recognition system to classify two classes of the index finger motions, flexion and rest. Combination of time-domain feature and autoregressive parameters is utilized to extract the features. Then SRDA is used to reduce the dimension of the features before being fed to the classifier. Two classifiers are evaluated, the original SVM and its enhancement, Self-Advice SVM (SA-SVM). The experimental result shows that SA-SVM improves the classification performance in all kernels tested. The experimental result shows that SA-SVM improves the classification performance by on average 0.63 % across ten subjects.

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