ISSN 2714-7533

Classification of Finger Movements Using EMG Signals with PSO SVM Algorithm

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ARTICLE INFO

Article history
Received September 17, 2022
Revised October 17, 2022
Accepted November 27, 2022

Keywords
EMG
PSO SVM
Finger movement

ABSTRACT

Electromyography (EMG) is a signal produced by human muscles when they contract or relax. This signal is widely used as a controller, for example, to control a robotic arm. This study aims to identify the pattern of finger movement in the form of finger movement using a bracelet-shaped device that has eight EMG sensors. This tool is placed on the lower right hand of a subject to get a signal from the EMG. This study uses the support vector machine (SVM) algorithm combined with the particle swarm optimization (PSO) method. For pattern recognition, the properties of the signal in the time domain are used. From this system, the success of pattern recognition is between 68% to 86%.

1. Introduction

The Robotics era is developing. Many humans innovate to help their sports, making manipulator robots to pick up goods in risky locations or flow items with excessive precision [1]. Robotic hands also enable to assist humans within the clinical field. Inside the clinical vicinity, many applications and tools are used to aid clinical technology and diagnose, treat, and prevent a disease or damage to parts of the human frame.

There is knowledge, namely biomechanics, in the medical area. This science applies the principles of generation, treatment, and analysis related to the movement of human activities to provide new technology, particularly electromyography (EMG). EMG can be defined as a signal that comes from human muscle groups during contraction or relaxation. The term in medication is referred to as electrophysiological. EMG signals determine the kingdom of human beings' muscle tissues and muscle cells. Furthermore, these signals enable to manipulation of mechanical devices, including controlling finger robots [2].

This finger robot is used to help people who have limitations in moving their fingers. To help them, a hand robot was made using the arm muscle controller. EMG signals are used to read muscle signal movements. In addition, an algorithm is also needed to analyze and classify these muscle movements with what the user wants [2].

Several types of sensors are used to capture EMG signals. Namely, they are placed under the skin or on the skin. In this study, an EMG sensor was mounted on the skin because it is more comfortable and easy to install. The sensor used is the Myo Armband. The signals captured by this sensor can then be obtained from several features. This feature can be divided into elements in the time domain

[3], frequency domain [4], or a combination of frequency and time domain. This study used sixteen-time domain features, which will be explained in the next section.

Previous studies have investigated algorithms that use EMG signals to recognize finger movements. Among them are using artificial neural networks [2], ANFIS [3], Support Vector Machine (SVM) [4], K-NN, and Naïve-Bayes [5]. The results obtained in previous studies received success ranging from 60% -80%. In this study, SVM will be combined with particle swarm optimization (PSO) to optimize the coefficients used in the SVM algorithm. It is hoped that by using this algorithm, better results will be obtained compared to previous studies.

The Myo Arm Band used in this experiment has eight myo sensors. Where this sensor can detect EMG signals, these signals are obtained from the Myo sensor placed on the skin containing the muscle to be measured. EMG. The data obtained need to be further processed for the data grouping process. This is because the input received will have a low success rate and require a longer processing time. Therefore, these data need further processing to obtain the signal features. For this study, the features in the time domain are used. Features in this domain are features commonly used by many researchers to classify a signal compared to features from other domains. One of the advantages of the time domain feature is that it computes faster than the frequency domain feature. This is because using the frequency domain requires processing to change from the time domain to the frequency domain first before getting the features. [6], [7]. The time domain features used in this experiment include:

Integrated EMG (IEMG) indicates an onset in a clinical application. The IEMG feature is defined as the sum of the absolute values of an EMG signal amplitude [8].

$$IEMG = \sum_{i=1}^{N} |x_i| \tag{1}$$

Where N is the number of data and xi is the amplitude at the time i. Next is the mean absolute value (MAV).

MAV is a time domain feature widely used in analyzing signals, including EMG [8].

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{2}$$

Root mean square (RMS) is a statistical property widely used to analyze signals in the time domain [8]. This feature is more or less similar to the Standard Deviation feature [9].

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{3}$$

Difference Absolute Standard Deviation Value (DASDV) this feature is almost the same as the RMS feature. DASDV can be said is a price of the standard deviation of a wavelength of a signal/wave [8].

$$DASDV = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (x_{i+1} + x_i)^2} \tag{4}$$

Simple square integral (SSI) is the sum of a signal's amplitude to the power of two [8].

$$SSI = \sum_{i=1}^{N} x_i^2 \tag{5}$$

The variance of this feature's EMG (VAR) can be said to be the mean of the square of the amplitude of a signal [8].

$$VAR = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2 \tag{6}$$

Modified mean absolute value type 1 (MAV1) is the development of the previous feature. Giving the weight function wi in the MAV Equation usually increases in the Equation to increase strength [8].

$$MAV1 = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i| \tag{7}$$

$$w_i = \begin{cases} 1, & if \quad 0.25N \leq i \leq 0.75N \\ 0.5, & else \end{cases}$$

Modified mean absolute value type 2 (MAV2) this feature is also an extension of the MAV formula such as MAV1. But the weight function w_i given in the Equation is continuous. One of the functions of this weight is to increase smoothness [8].

$$MAV1 = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i| \tag{8}$$

$$wi = \begin{cases} 1, & if\ 0.25N \leq i \leq 0.75N \\ 4i/N, & else\ if\ i < 0.25N \\ 4(i-N)/N, & otherwise \end{cases}$$

Waveform length (WL) is the feature to measure the EMG complexity. This selection can be explained as the cumulative duration of the EMG signal waveform over a time phase [8].

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{9}$$

Hjorth Activity (Hjorth 1) describes the signal's power and variance of the function of time. Also, this feature enables representing the surface of the power spectrum in the frequency domain [10].

$$Hjorth\_1 = \sigma_x^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - 1)^2 \tag{10}$$

Hjorth Mobility (Hjorth 2) describes the mean of the frequency or the proportion of standard deviations of the power spectrum [10].

$$Hjorth\_2 = \frac{\sigma_{x'}}{\sigma_x} \tag{11}$$

Hjorth Complexity (Hjorth 3) this feature describes the frequency shift. This parameter compares the measured signal with a pure sine wave, where the value is centered on the number 1 if many signals are similar [10].

$$Hjorth\_3 = \frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x''}/\sigma_x} \tag{12}$$

An autoregressive coefficient is a general approach for modeling univariate time series in Equation form [8].

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_n y_{t-n} + \varepsilon_t = \sum_{i=1}^{N} a_1 y_{t-1} + \varepsilon_t \tag{13}$$

Support Vector Machine (SVM) is a classification technique that requires version education to test samples [9]. SVM affords education as a supervised mastering approach. This classifier is straightforward to recognize as it builds a hyperplane among the one-of-a-kind classes that need to be categorized. The classification used may be the linear or non-linear feature. In a linear SVM, elegance education samples may be separated linearly. but for a few instances, the pattern can't be labeled linearly. For such instances, non-linear classification is exploited [11].

Kernel functions are used to construct linear thru non-linear ameliorations or mappings to locate the best elegance for the selection area [11]. SVM implements that the input vector is non-linearly mapped to the excessive-dimensional feature area. The enter facts are xi (i=1,2,…, M), and M is the wide variety of samples. It is assumed that there are instructions, particularly the high-quality and bad lessons. The two categories are denoted by y1=1 for the advantageous and y1=-1 for the wrong kinds. For linear facts, it's far viable to determine the hyperplane aircraft characteristic of f(x)=zero setting apart the given records as in (14).

$$f(x) = w^T x + b = \sum_{i=1}^{M} w_i x_i + b = 0 \quad (14)$$

The dimensional -M vector w and scalar b are used to decide the location of the separated hyperplane. Its miles were created using the choice function of the signal f(x) to categorize the input records in high-quality and poor instructions. The constraint should be met by setting apart the hyperplane, which can be written at (15).

$$y_i\, f(x_i) = y_i(w^T x_i + b) \geq 1 \text{ for } i = 1,2,\dots,M \quad (15)$$

The finest dividing hyperplane is the most distance between the aircraft and the nearest information, i.e., the maximum margin created through splitting the hyperplane. SVM attempts to put a linear boundary among the two training, directing them so that dashes are maximized. In addition, SVM tries to direct the most distance among the border and the closest facts factor in each class. The boundary is inside the middle of the margin between the 2 points. The assist vector is the nearest data point used to determine the margin. on this linear machine, the vector ordinary to the hyperplane is w, and the perpendicular distance from the hyperplane to the starting place is $\frac{-b}{|w|}$.

Noise with slack variable ξ_i and errors penalty C, the most advantageous hyperplane that separates the records may be calculated using Equations (16) and (17)

$$\text{Minimize } \frac{1}{2}||w||^2 + C \sum_{i=1}^{M} \xi_i \quad (16)$$

$$\text{With} \begin{cases} y_i(w^T x_i + b) \geq 1 - \xi_i, i = 1,\dots,M \\ \xi_i \geq 0, i = 1,\dots,M \end{cases} \quad (17)$$

Where ξ_iMeasures the distance between the margins, the calculation can be simplified to a dual Lagrangian problem as in (18) using the Kuhn-Tucker condition.

$$\text{Min } L(w,b,\alpha) = \frac{1}{2}||w||^2 - \sum_{i=1}^{M} \alpha_i y_i (w.x_i + b) + \sum_{i=1}^{M} \alpha_i \quad (18)$$

The task is to minimize Equations (16) and (17) for w and b. The saddle point at the optimal point can be calculated using Equations (18) and (19)

$$\text{Maximize } L(\alpha) = \sum_{i=1}^{M} \alpha_{i-} \frac{1}{2} \sum_{i=1}^{M} \alpha_i \alpha_j\, y_i x_i\, x_j \quad (18)$$

$$\alpha_i = 0, i = 1,\dots,M$$

$$\text{With } \sum_{i=1}^{M} \alpha_i y_i \quad (19)$$

Solving the multiple optimization problems, we get the coefficient αi which is required to express w to solve Equations (16) and (17). The non-linear decision function becomes Equation (20)

$$f(x) = sign \ \sum_{i,j=1}^{M} \alpha_i\, y_i \left(x_i\, x_j\right) + b \quad (20)$$

SVM can be used in non-linear classification by application kernel functions. The data is mapped into a high-dimensional feature space using a non-linear vector function of $\Phi\ (x) = (\phi_1(x), \dots, \phi_i(x))$. The decision function can be calculated using Equation (21)

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$$f(x) = sign \quad \sum_{i,j=1}^{M} \alpha_i . y_i \left(\Phi^T(x_i).\Phi(x_j)\right) + b \tag{21}$$

High dimensions will cause overfitting and computational problems due to large vectors. The problem can be solved with the kernel function $K(x_i, x_j) = \left(\Phi^T(x_i).\Phi_j(x_j)\right)$.Decision function like Equation (22)

$$f(x) = sign \left(\sum_{i,j=1}^{M} \alpha_i\, y_i K\left(x_i\, x_j\right) + b\right) \tag{22}$$

The kernel functions often used in SVM are shown in Table 1.

Table 1. Kernel Functions in SVM

Name	$K(x.x_i)$,i= 1,2 ,…,N
Linear	$K(x, x_i) = (x^T x_i)$
Polynomial	$K(x, x_i) = (x^T x_i + 1)^d$
Gaussian RBF	$K(x.x_i) = exp\left(-\frac{\lVert x - x_i \rVert}{2\sigma^2}\right)$
Sigmoid	$K(x.x_i) = \tanh\,(\beta_0 x^T x_i - \beta_1)$

From previous studies, the Gaussian RBF kernel is the most suitable for using SVM [12].

PSO is an optimization algorithm to get an idea of animal behavior where an individual's behavior will affect others. Namely, the behavior of fish or birds. Where a group of bird/fish populations searches for a place, they exploit an individual bird/fish. If one of them can find the shortest path/right, the group will follow that path. In this algorithm, the term swarm comes from the population.

In comparison, the term particle comes from the individual. Each particle changes position with speed adapted from the search area. Then this algorithm will save it as the best place/position it has ever passed [13], [14].

J. Kennedy and R. C. Eberhart. They are introducing the PSO model. Initially, this algorithm was used to optimize a multivariable by taking the example of a flock of birds that will look for food sources. The group has a fixed number, with each individual having a random location. Each moves in a particular space and remembers his position. Each individual remembers the best position he has ever been in. The information is conveyed to other individuals so that other particles will move through the path by adjusting the place and speed of each [15].

This modeling can be imitated in a space with a specific dimension. Each loop/iteration can bring the particle to the target destination. The algorithm will stop if the target is met or the maximum iteration is reached

The development of a PSO model can be divided into several parts. The first part is the initiation part. Where the initial position of each particle and also the speed is determined in advance randomly. However, the rate is within the maximum and minimum limits to determine its value using Equations (23) and (24).

$$x_0^t = \text{xmin} + \text{rand}(\text{xmax} - \text{xmin}) \tag{23}$$

$$v_0^t = \text{xmin} + \text{rand}(\text{xmax} - \text{xmin}) \tag{24}$$

Where :

x_0^t = Initial position

v_0^t = Initial velocity

xmin = Upper limit

xmax = Lower limit

rand = Random value between 0 and 1

Then is updating the position and velocity of each particle. The position and speed is updated with Equation (25), where each particle moves to find the most optimal solution, where they will move towards the previous best direction.

$$V_{ij}(t+1) = W * V_{ij}(t) + C_1 * Rand_1 * \left(Pbest_{ij}(t) - P_{ij}(t)\right) + C_2 * Rand_2 \left(Gbest_{ij}(t) - Pij(t)\right) \quad (25)$$

Where:

t = Iteration

Vij= Particle velocity i in jth dimension (the value is limited between [- Vmax, vmax])

pij = position of particle i on j dimension (the value is limited between [-pmax, pmax])

Pbestij= pbest position of particle i in jth dimension

gbestij = gbest position of the jth dimension

w = inertia weight (balance global and local exploration)

rand1 and rand2= random function in the range [0, 1]

β = constraint factor to control weight speed (value to 1) c1 and c2 are personal and social learning factors (value to 2)

2. Methods

In this study, a Myo arm band sensor was used by a subject. The sensor is connected to a computer with an algorithm used. The algorithm is an algorithm for reading data from sensors and also an algorithm for training and testing with SVM PSO with the RapidMiner program. A screen is used to show the results of the test. Fig. 1 shows a block diagram of the system used. While in Fig. 2 shows the flow of the experiments carried out.

A subject is a man who has an active right hand. The subject is 22 years old. He has no muscle or nerve disorders. The sensor is placed on the lower right arm of the subject, as shown in Fig. 3. Sensor number 4 is placed parallel to the palm of the back of the subject (see Fig. 3). In data collection, the arm of the subject is placed on the arm of the table. This is done to reduce the interference signal from the unwanted movement of the subject's arm. Subjects were asked to move each finger open and close ten times in twenty seconds. Figure 4 shows the EMG signal from sensor number eight for each finger movement. The signals were then processed on a computer. Each signal generated by the finger is separated into ten signals that signify movement per finger. The signal is processed to obtain features in the time domain.

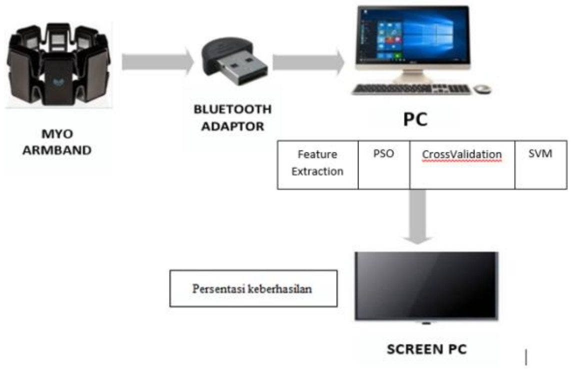


Figure 1. Blok Diagram of the system

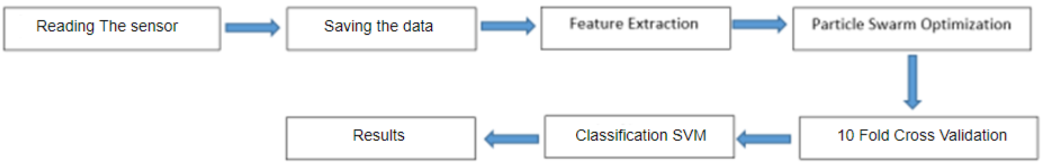


Figure 2. Experimental flow

Figure 3. the position of the Myo Armband on the arm

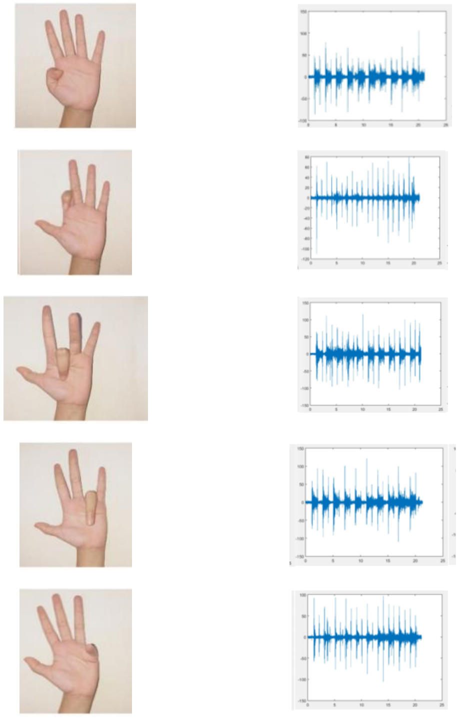
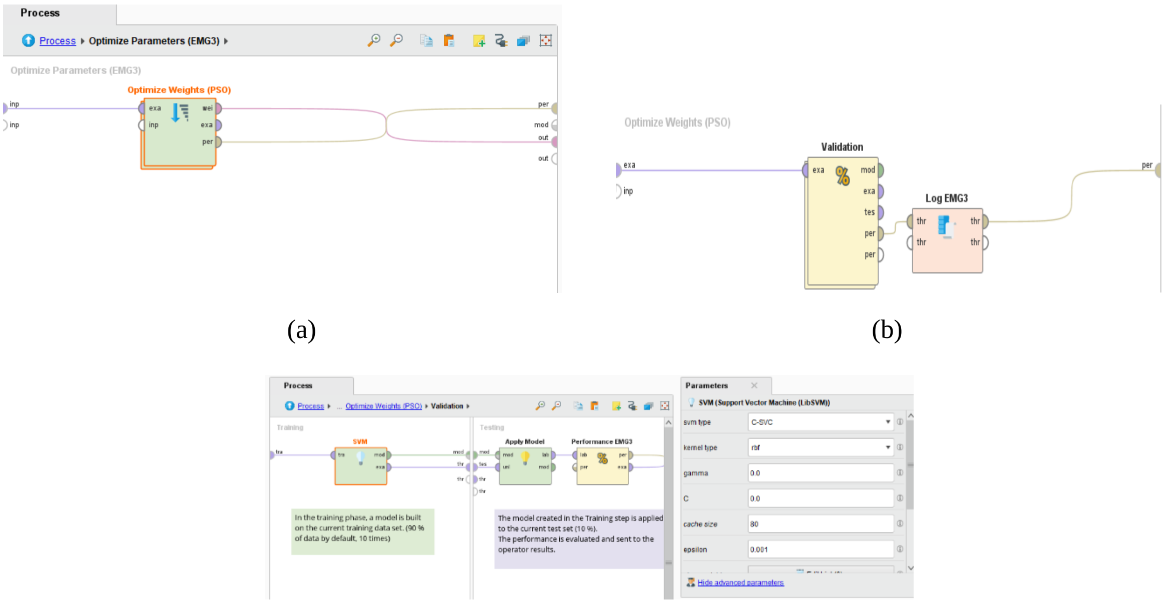


Figure 4. Finger movement pattern When EMG signal data is obtained

To test the reliability of the PSO SVM algorithm, it is evaluated and validated using cross-validation. Where the PSO SVM algorithm is processed using a RapidMiner program. Fig. 5 shows the program from the PSO SVM used in RapidMiner.



(a) (b)

(c)

Figure 5. (a) PSO processing (b) Validation from PSO (c) SVM and cross validasi

3. Result and discussion

After the feature extraction dataset is obtained, the feature extraction data is then evaluated and validated using cross-validation (see Fig. 6). This process aims to determine the capabilities of the specified algorithm or model. To do this process, the data is separated into two parts. One part is used as learning data/first data, and one part is part for validation/second data. To generate the model, the first data is used. The resulting model will be validated with the second data. In accordance with Fig 6, the comparison of the first and second data is 9:1. The red sections are the test data, and the white cells are the training data. In this study, the K value was 10, and 10 experiments were carried out for each hand movement. Five patterns of hand movement produce 50 datasets. The final matrix of the dataset includes 13 feature extractions. The result is a 16 x 50 matrix. The dataset is then inputted into the PSO to assign weights to each attribute/feature. After getting the weights, the dataset is inputted into cross-validation to be used as learning and evaluation/validation. The results are then classified using SVM to get a percentage of the accuracy of the algorithm model.

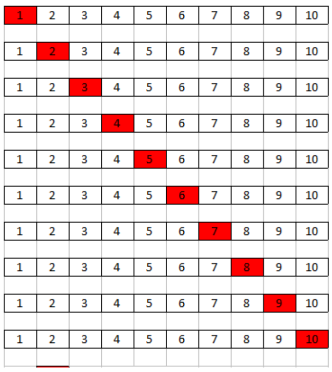


Figure 6. Scheme 10 fold CrossValidation

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Using the RBF kernel on SVM and several parameters set to C and Gamma with the minimum limit criteria being 0, the maximum limit being 1, the minimum population being 5 and the maximum population being 10, the results are shown in Table 2. The results showed that the accuracy was better if the population value was 10, with accuracy at EMG 3 being 86%, EMG 4 being 76%, and EMG 8 being 66%.

Tabel 2. Comparison of three sensors

Sensor	Pop	Accuracy	Gamma	C
EMG 3	5	84.00%	0.1	0.4
	10	86.00%	0.8	0
EMG 4	5	74.00%	0.4	0.3
	10	78.00%	0.9	1
EMG 8	5	64.00%	0.7	0
	10	66.00%	0.9	0.8

4. Conclusion

In this article, a system is tried to check the PSO SVM algorithm's ability to classify finger movements. A muscle sensor has eight sensors. These sensors detect the EMG signal generated when moving each finger. This system is able to classify finger movement patterns with an accuracy rate of 86% for sensor 3, 78% for sensor 4, and 66% for Sensor 8 with a population of 10. Accuracy can be increased by changing the population parameters on the PSO. The higher the population raised, the higher the percentage of accuracy obtained. This system will have the potential to be tested in real-time and applied to the control of a hand robot.

Acknowledgment

This research was funded by the DRPM research fund

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