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COMPARISON BETWEEN PCA-SVM WITH PSO-SVM FOR RECOGNIZE EMG SIGNAL

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Abstract

This study compares two machine learning approaches, PCA-SVM and PSO-SVM, for classifying electromyographic (EMG) signals to recognize hand gestures. Using a Myo sensor bracelet, EMG data were gathered from eight male subjects, ages 19-22, each performing five distinct gestures. Time-domain features of the EMG signals were analysed, with PCA-SVM reducing dimensionality to the three most significant principal components, while PSO-SVM optimized SVM parameters for improved performance. Results indicate that PSO-SVM achieved approximately 3% higher accuracy than PCA-SVM, highlighting its potential for applications requiring precise gesture recognition, such as robotic control and prosthetics. The findings underscore PSO-SVM's higher classification accuracy, though with slightly increased processing time due to parameter optimization. This modest improvement suggests PSO-SVM's value in real-time EMG applications, where accuracy is critical. Limitations related to sample size and time-domain-only features suggest avenues for future work, including exploring additional feature domains and larger datasets to enhance the robustness of EMG-based gesture recognition systems.

Keywords: Electromyographic (EMG) signals, Gesture recognition, Myo sensor, Particle Swarm Optimization (PSO), Principal Component Analysis (PCA), Support Vector Machine (SVM).

1.Introduction

The field of robotics is increasingly dedicated to developing technologies that assist human activities, particularly those that demand precision or take place in hazardous environments. This includes applications such as object manipulation in confined spaces, remote operations, and risk reduction for operators [1]. In the medical domain, EMG-based systems are pivotal in diagnosing, detecting, and aiding individuals with physical impairments [2-5]. Biomechanics, specifically, studies the electrical signals produced by muscle movements, known as electromyography (EMG). When muscles contract or relax, they emit these EMG signals, which are instrumental in controlling robotic devices and prosthetics [6].

EMG signals provide a means for individuals with hand amputations or other disabilities to regain functional control over artificial hands, improving their ability to perform daily tasks [7]. Two main approaches to capturing EMG signals exist: invasive methods that insert sensors into the skin and non-invasive methods that place sensors on the skin's surface [1, 2]. Although the invasive approach yields detailed data, the non-invasive technique is generally preferred for comfort and accessibility, despite requiring advanced signal processing to improve accuracy [8].

Accurate gesture recognition using EMG signals relies on extracting features from these signals, which fall into three primary domains: frequency, time, and a combination of both. Features like Mean Frequency and Median Frequency are typical in the frequency domain [9], while in the time domain, common features include the Absolute Value of the signal amplitude and the Mean Absolute Value (MAV) [10]. Time-frequency domain features, such as Wavelet Packet Transforms, are also commonly applied to enhance accuracy in gesture recognition [11-13].

A range of algorithms has been explored for hand gesture recognition, including Artificial Neuro-Fuzzy Inference Systems (ANFIS) [6], Linear Discriminant Analysis (LDA) [14], Neural Networks (NN) [15], Fuzzy classifiers [16], and K-Nearest Neighbours (K-NN) [17, 18]. Among these, Support Vector Machines (SVM) have shown strong performance in recognizing patterns within myoelectric data. The SVM algorithm excels at identifying complex patterns by identifying a hyperplane in n-dimensional space, which serves to classify different input features effectively [19]. Studies have demonstrated that SVM outperforms various classifiers, including Artificial Neural Networks (ANN) and LDA, particularly in analysing EMG data [20-24].

This study aims to enhance gesture recognition accuracy by comparing two specific SVM-based techniques: PCA-SVM, which combines Principal Component Analysis (PCA) with SVM to reduce dimensionality and optimize feature selection, and PSO-SVM, which leverages Particle Swarm Optimization (PSO) to refine SVM parameters. Both methods use time-domain EMG signal characteristics due to their computational efficiency in pattern classification.

A Myo armband sensor was employed to collect EMG data from eight participants performing specific gestures, with each method trained on 70% of the data and tested on the remaining 30%. Our study provides insights into the comparative performance of these approaches, with PSO-SVM showing a slight accuracy improvement over PCA-SVM. These findings contribute to the field of gesture recognition by highlighting the potential of PSO-SVM in real-time applications that require high precision, such as assistive robotics and medical devices.

2. Methods

This study involved eight male participants aged 19-22, each performing five distinct finger gestures while wearing a Myo armband sensor on their dominant arm. The sensor, positioned on the superficial flexor digitorum muscle, recorded EMG signals at a sampling rate of 200 Hz, transmitting the data to a computer for analysis. The system setup, shown in Fig. 1, ensured consistency by positioning the participants' arms on an armrest to reduce fluctuations in signal quality. Fig. 2(a) illustrates the EMG waveform for each gesture, and Fig. 2(b) shows the armband positioned on the participant's arm.

Fig. 1. The System's block diagram.

(a) (b)

Fig. 2. (a) EMG Sensors, (b) Arm with the bracelet.

Time-domain features were selected for their computational efficiency and reliability in classification tasks. These features included Root Mean Square (RMS), Mean Absolute Value (MAV), and Variance, calculated using the following equations:

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

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

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

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

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

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

$$\mathrm{MAV1}=\frac{1}{N}\sum_{i=1}^{N}w_i|x_i|$$
$$w_i=\begin{cases}1, & if \quad 0.25N\le i\le 0.75N\\ 0.5, & else\ if\end{cases} \tag{7}$$

$$\mathrm{MAV2}=\frac{1}{N}\sum_{i=1}^{N}w_i|x_i|$$
$$w_i=\begin{cases}1, & \text{if } 0.25N\le i\le 0.75N\\ 4i/N, & \text{else if } i<0.25N\\ \frac{4(i-N)}{N}, & \text{otherwise}\end{cases} \tag{8}$$

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

$$y_t=a_1y_{t-1}+a_2y_{t-2}+\ldots+a_ny_{t-n}+\varepsilon_t=\sum_{i=1}^{N}a_1y_{t-1}+\varepsilon_t \tag{10}$$

$$\mathrm{Hjorth\_1}=\sigma_x^2=\frac{1}{N}\sum_{i=1}^{N}(x_i-1)^2 \tag{11}$$

$$\mathrm{Hjorth\_2}=\frac{\sigma_{x'}}{\sigma_x} \tag{12}$$

$$\mathrm{Hjorth\_3}=\frac{\sigma_{x''}/\sigma_{x'}}{\sigma_{x''}/\sigma_x} \tag{13}$$

These equations facilitated an efficient feature extraction process, and the values of each feature are provided in Table 1. To reduce the dimensionality of the feature set, Principal Component Analysis (PCA) was used in the PCA-SVM model. PCA selected the three principal components with the highest eigenvalues, capturing the most significant aspects of the data. The transformed features are detailed in Table 2, with PCA reducing the complexity while preserving the variance in the EMG signals.

In the PSO-SVM model, Particle Swarm Optimization was used to optimize the SVM's RBF kernel parameters, gamma and C, enhancing classification accuracy. The training phase applied 70% of the data, leaving 30% for testing. The Gestures of the hand for this study can be seen in Fig. 3. Figures 4(a) and 4(b) display the flowcharts for PCA-SVM and PSO-SVM models, respectively, summarizing the steps of feature extraction, dimensionality reduction, parameter optimization, and classification.

Table 1. Extracting features from the initial recording of EMG signal 3.

	a	b	c	d	e
RMS	15.55	9.28	24.17	21.49	10.03
VAR	242.32	86.21	584.82	462.3799	100.79
MAV2	5.063	1.579	8.636	6.496462	1.963773
MAV2	10.68	5.32	15.65	14.5351	5.531128
DASDV	24.82	14.58	38.68	35.72881	15.22451
SSI	24136	91730	765534	486886	103520
MAV1	7.52	3.30	10.84	10.18311	3.429475
IEMG	10654	5674	20502	15320	5686
AR	0.22	0.05	0.13	0.25	0.26
Hjorth1	241.7	85.9	584.70	462.12	100.53
Hjorth2	1.59	1.57	1.60	1.66	1.51
Hjorth3	1.1	1.13	1.12	1.08	1.13
WL	3	2	10	2	2

Table 2. Using PCA.

	a	b	c	d	e
PC-1	0.254	0.599045	0.037573	0.749	-0.1183
PC-2	0.0965	0.50934	-0.37983	-0.310	0.700435
PC-3	0.806	-0.39924	-0.43013	0.0628	-0.02628

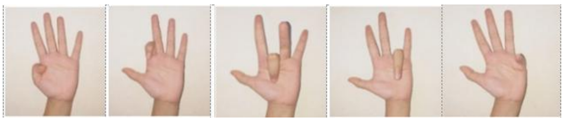
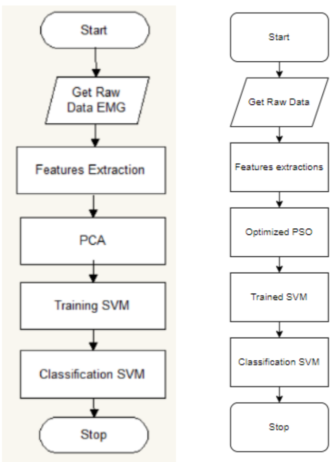


Fig. 3. Gestures of the hand for this study.



(a) (b)

Fig. 4. Flowchart (a) PCA-SVM, (b) PSO-SVM.

3. Results

All the subjects were tested for all the poses. The raw data of all the sensors is then processed in the computer to obtain all the features of these data. Figure 5 shows data from sensor no 3 from one of the subjects. This data will be divided into ten parts for each pose. Iterative processing will be applied to extract the temporal domain characteristics of the signals.

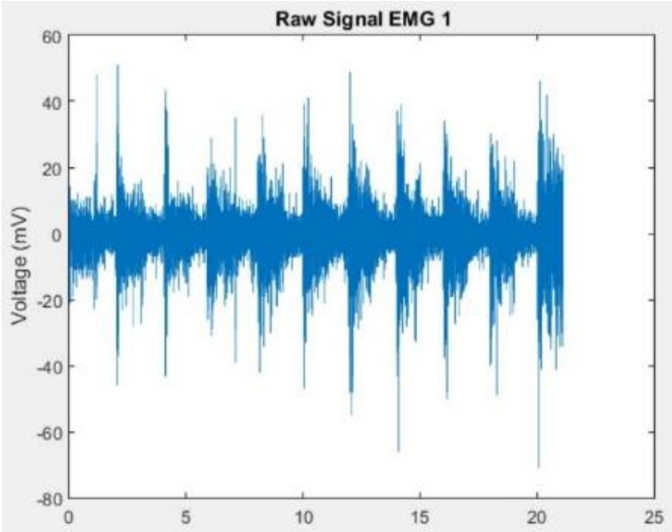


Fig. 5. Raw data of the EMG in sensor 3.

For the PCA SVM algorithm, the features are selected and reduced. From thirteen features are reduced and become only three new features. The selection of these three variables was obtained from the most significant eigenvalues. Where this eigenvalue corresponds to the most informative variable. Tables 1 and 2 show the data of the first capture of sensor 3 before and after the PCA process, respectively (Where a is the thumb, b is the index, c is the middle finger, d is the ring, and e is the little finger movement.). New data are trained, and the trained SVM is. The results of the SVM combined with PCA are shown in Table 3, with the average of the rates being around 83.6%.

Table 3. The effectiveness of the SVM PCA algorithm.

Subject No.	Percentage of Each Gesture					Average
	a	b	c	d	e	
1	80.3	81.6	79.6	78	77.6	79.5
2	74.3	76.7	77.1	79	75.6	76.6
3	87.5	83.5	82.4	81	82.2	83.38
4	95.2	97.1	92.3	93	90.7	93.58
5	91.3	93.6	89	90	88.3	90.52
6	89.5	88.9	84.7	86	83.4	86.4
7	90.3	86.4	85.8	87	89.2	87.8
8	71.3	73.5	73.4	69	70.2	71.38

For the PSO-SVM algorithms, we used five particles as the PSO parameters. By using this algorithm, the selected features are three of the thirteen previous features. When the values of gamma and C are obtained, the success rate can be seen in Table 4. The average of all percentage values is around 86.7%.

Table 4. The successful rate of the SVM PSO algorithm.

Subject No.	Percentage of Each Gesture					Average
	a	b	c	d	e	
1	82.4	81.7	80.2	79.2	78.3	80.36
2	76.9	77.3	79.2	78.8	77.3	77.9
3	89.5	85.1	84.6	82.6	83.3	85.02
4	96.5	98.4	95.5	94.1	91.2	95.14
5	95.2	93.8	91.4	93.5	90.2	92.82
6	90.8	89.5	86.5	88.5	89.1	88.88
7	95.2	90.4	89.6	91.1	92.2	91.7
8	81.3	83.4	81.6	80.3	82.2	81.76

4. Conclusions

This study compared PCA-SVM and PSO-SVM to classify EMG signals to recognize hand gestures. Both methods used EMG data from a Myo armband, with PCA-SVM reducing features via PCA and PSO-SVM optimizing SVM parameters through Particle Swarm Optimization. Results show that PSO-SVM achieved approximately 3% higher accuracy than PCA-SVM, making it more suitable for precision applications like robotic control, despite slightly higher computational costs. The findings suggest that parameter optimization is crucial for improving EMG classification, especially for real-time systems. Future research could enhance model performance by integrating other dimensionality reduction methods, incorporating diverse user data, and refining optimization for faster, real-time applications. This study supports PSO-SVM as a promising approach for EMG-based gesture recognition, advancing assistive technology development.

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References

1. Caiza, G.; Garcia, C.; Naranjo, J.E.; and Garcia, M. (2020). Flexible robotic teleoperation architecture for intelligent oil fields. *Heliyon*, 6(4), 1-13.
2. Mariappan, M.; Ramu, V.; Thiam, B.K.T.; Ganesan, T.; and Nadarajan, M. (2014). Medical Tele-diagnosis Robot (MTR)-internet based communication & navigation system. *Applied Mechanics and Materials*, 490, 1177-1189.
3. Yu, S.; Perez, H.; Barkas, J.; Mohamed, M.; Eldaly, M.; Huang, T.H.; and Edwards, D.J. (2019). A soft high force hand exoskeleton for rehabilitation and assistance of spinal cord injury and stroke individuals. *Proceedings of the* 2019 *Design of Medical Devices Conference*, Minnesota, USA, 15-18.
4. Altion, S.; Yoshifumi, N.; and Koichi, N. (2006). A humanoid robot to prevent children accidents. *Proceedings of the* 12th *International Conference*, *VSMM* 2006, Xi’an, China, 18-20.

5. Triwiyanto, T.; Luthfiyah, S.; Sumber, S.; Pudji, A.; Kholiq, A.; Utomo, B.; and Titisari, D. (2021). A review: Sensory system, data processing, actuator type on a hand exoskeleton design. *Journal of Biomimetics*, *Biomaterials and Biomedical Engineering*, 50, 39-49.
6. Anwar, T.; and Al Jumaily, A. (2016). Estimation of angle based on EMG using ANFIS. *Proceedings of the* 2016 *IEEE Symposium Series on Computational Intelligence* (*SSCI*), Athens, Greece, 1-6.
7. Hasan, H.N. (2016). A wearable rehabilitation system to assist partially hand paralyzed patients in repetitive exercises. *Journal of Physics*: *Conference Series*, 1279, 1, 012040.
8. Õunpuu, S.; DeLuca, P.A.; Bell, K.J.; and Davis, R.B. (1997). Using surface electrodes for the evaluation of the rectus femoris, vastus medialis, and vastus lateralis muscles in children with cerebral palsy. *Gait & Posture*, 5, 211-216.
9. Angelova, S.; Ribagin, S.; Raikova, R.; and Veneva, I. (2018). Power frequency spectrum analysis of surface EMG signals of upper limb muscles during elbow flexion-A comparison between healthy subjects and stroke survivors. *Journal of Electromyography and Kinesiology*, 38, 7-16.
10. Esa, N.M.; Zain, A.M.; and Bahari, M. (2018). Electromyography (EMG) based classification of finger movements using SVM. *International Journal of Innovative Computing*, 8(3), 9-16.
11. Yousif, H.A.; Zakaria, A.; Rahim, N.A.; Salleh, A.F.B.; Mahmood, M.; Alfarhan, K.A.; and Hussain, M.K. (2019). Assessment of muscles fatigue based on surface EMG signals using machine learning and statistical approaches: A review. *Proceedings of the* 5th *International Conference on Man Machine Systems*, Pulau Pinang, Malaysia, 26-27.
12. Pancholi, S.; and Joshi, A. (2020). Improved classification scheme using fused wavelet packet transform based features for intelligent myoelectric prostheses. *IEEE Transactions on Industrial Electronics*, 67, 8517-8525.
13. Guo, X.; Yang, P.; Li, Y.; and Yan, W.L. (2006). The SEMG analysis for the lower limb prosthesis using wavelet transformation. *Proceedings of the* 26th *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Francisco, CA, USA, 341-344.
14. Zhang, D.; Xiong, A.; Zhao, X.; and Han, J. (2012). PCA and LDA for EMG-based control of bionic mechanical hand. *Proceedings of the* 2012 *IEEE International Conference on Information and Automation*, Shenyang, China, 960-965.
15. Gogić, A.; Miljkovic, N.; and Đurđević, Đ. (2016). Electromyography-based gesture recognition: Fuzzy classification evaluation. *Proceedings of the* 3rd *International Conference on Electrical, Electronic and Computing Engineering*, Zlatibor, Serbia, 23-27.
16. Kaya, E.; and Kumbasar, T. (2018). Hand gesture recognition systems with the wearable myo armband. *Proceedings of the 6th International Conference on Control Engineering & Information Technology* (*CEIT*), Istanbul, Turkey, 1-6.
17. Phinyomark, A.; Phukpattaranont, P.; and Limsakul, C. (2011). A review of control methods for electric power wheelchair based on electromyography signals with special emphasis on pattern recognition. *IETE Technical Review*, 28(4), 316-326.

18. Simatupang, I.; Pamungkas, D.; and Risandriya, S. (2021). Naïve bayes classifier for hand gestures recognition. *Proceedings of the 3rd International Conference on Applied Engineering-ICAE*, Batam, Indonesia, 110-114.
19. Oskoei, M.; and Hu, H. (2008). Support vector machine-based classification scheme for myoelectric control applied to upper limb. *IEEE Transactions on Biomedical Engineering*, 55, 1956-1965.
20. Goen, A.; and Tiwari, D.C. (2016). Classification of the myoelectric signals of movement of forearms for prosthetic control. *Journal of Medical and Bioengineering*, 5, 76-84.
21. Purushothaman, G.; and Vika, R. (2018). Identification of a feature selection based pattern recognition scheme for finger movement recognition from multichannel EMG signals. *Australasian Physical & Engineering Sciences in Medicine*, 41, 549-559.
22. Roldan-Vasco, S.; Restrepo-Agudelo, S.; Valencia-Martinez, Y.; and Orozco-Duque, A. (2018). Automatic detection of oral and pharyngeal phases in swallowing using classification algorithms and multichannel EMG. *Journal of Electromyography and Kinesiology*, 43, 193-200.
23. Dhindsa, I.S.; Agarwal, R.; and Ryait, H.S. (2019). Performance evaluation of various classifiers for predicting knee angle from electromyography signals. *Expert Systems*, 36, 1-14.
24. Caesarendra, W.; and Irfan, M. (2018). Classification method of hand gesture based on support vector machine. *Computer Engineering and Applications*, 7(3), 179-190.