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Performance Comparison of Artificial Neural Network and Gaussian Mixture Model in Classifying Hand Motions by Using sEMG Signals

ULVI BASPINAR*, HUSEYIN SELCUK VAROL, VOLKAN YUSUF SENYUREK

Technical Education Faculty, Electronics & Computer Education Department, Marmara University, Istanbul, Turkey

In this study, a home-made four channel sEMG amplifier circuit was designed for measuring of sEMG signals. The measured sEMG signals were recorded on to a computer with help of a DAQ board. The recorded sEMG signals were filtered first with a high-pass filter and afterwards a wavelet based filtering was applied to remove unwanted noises. Before applying of the wavelet based filtering, it was first determined which wavelet type, threshold selection rule and threshold would be suitable for the denoising process. As a second step, the recorded and denoised signals' features were extracted. For classification of motions 8 time domain and 2 frequency domain features were used individually and in combinations. Lastly, seven different motions were classified and their classification performances were compared. In this study, classification rates of ANN and GMM classifiers were compared as regards features.

K e y w o r d s: hand motion classification, artificial neural network, gaussian mixture model

1. Introduction

The surface electromyography signals have been widely used in bio-medical robotic applications [1, 2] including diagnoses of neuromuscular diseases, controlling of assistive devices like prosthetic devices and Human Computer Interface (HCI). However, the most difficult part in developing of the myoelectric based control interfaces is the pattern recognition of the sEMG signals. In Fig. 1, the general block diagram of the sEMG pattern recognition system is shown. The system includes three major blocks.

* Correspondence to: Ulvi Baspinar, Technical Education Faculty, Electronics & Computer Education Department, Marmara University, Istanbul, Turkey, e-mail: ubaspinar@marmara.edu.tr
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The first is preprocessing and conditioning block. The second is feature extraction block and the third is pattern recognition block.

Recording of biomedical signals from the body surface often contains a substantial noise component. This noisy signal can severely impair resolution of biomedical recordings. Major types of noise, artifact and interference in recorded sEMG signal are electrode noise, electrode and cable motion artifact, power line interference, thermal noise derived from electronic amplification systems and other electrical signals produced by heart and nervous system [3]. Conventional filtering techniques such as low pass, high pass and band pass filtering can be used for reducing of line interference, thermal noise etc. or choosing a good electrode and instrument can reduce unwanted artifacts [4]. However, conventional methods can not remove random noise within the active EMG signal's spectrum band (20 Hz–500 Hz).

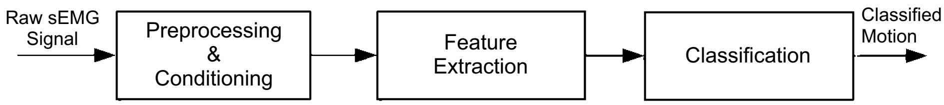

Fig. 1. The general block diagram of pattern recognition system

Recently, novel methods such as wavelet and Empirical Mode Decomposition (EMD) have been successfully applied to noise removal from sEMG signals [5, 6]. Especially, wavelet based denoising methods provide more successful results [7].

Another difficulty in pattern recognition is selecting the right features. Many researchers have used time domain and time-frequency domain features in their applications and studies [8–10]. While, in 1970s, mean absolute value and variance [11] were used as feature, after 1990s Hudgins et al. [12] showed that there is a considerable structure in the myoelectric signal during the onset of a contraction and further works[13] demonstrated that transient EMG signals have a greater classification capacity than steady-state signals.

Pattern recognition of the sEMG is essential in developing of myoelectric control based interfaces, so in order to achieve high recognition accuracy, a number of the EMG pattern recognition methods have already been proposed. Within these methods, artificial neural networks [12], fuzzy classifiers [8], wavelet transform based multistage recognition [14] and modern statistical classifiers [15], including Gaussian mixture models are most widely used classifying methods.

Hudgins et al. [12] succeeded in classifying four gestures(elbow extension, elbow flexion, wrist pronation and wrist supination) which were measured at four subjects with 90% accuracy by the use of ANN. Chan et al.[8] used the same method as Hudgins et al. and the data sets from the same four subjects and achieved similar classification results to those reported by Hudgins's paper using Fuzzy classifier instead of ANN. In another study, realized by Yonghong et al. [15] six different motions (wrist flexion, wrist extension, forearm supination, forearm pronation, hand open, and hand close) have been classified using the GMM with the accuracy of 96%.

In this study, we have performed classification of seven motions namely, hand open, hand close, spherical grasp, cylindrical grasp, precision hold, wrist supination and wrist pronation. For the classification of the motions two methods, ANN and the GMM, were used and their classification performances were compared with each other.

2. Materials and Methods

The surface EMG signals were collected from four people aged from 21 to 30. Bipolar electrodes were placed over Brachioradialis, Flexor Carpi radialis, Flexor Carpi ulnaris and Flexor Digitorum muscles and the reference electrode on the wrist. The signals were acquired using a home-made four channel sEMG amplifier. AD 8295 precision instrumentation amplifier was preferred for the amplification of sEMG signals and the gain factor was set to 200. Figure 2 shows the schematics of the sEMG amplifier circuit that is used in the study. To suppress higher frequencies above 500 Hz, a two pole Sallen-Key low-pass filter was connected at the output of the amplifier. The filtering frequency of the low-pass filter can be adjusted by changing R1, R2 resistors and C1, C2 capacitors. The electrodes, used in the study were Ag/AgCl bipolar passive disposable electrodes (Myotronics Inc.) of 1mm diameter

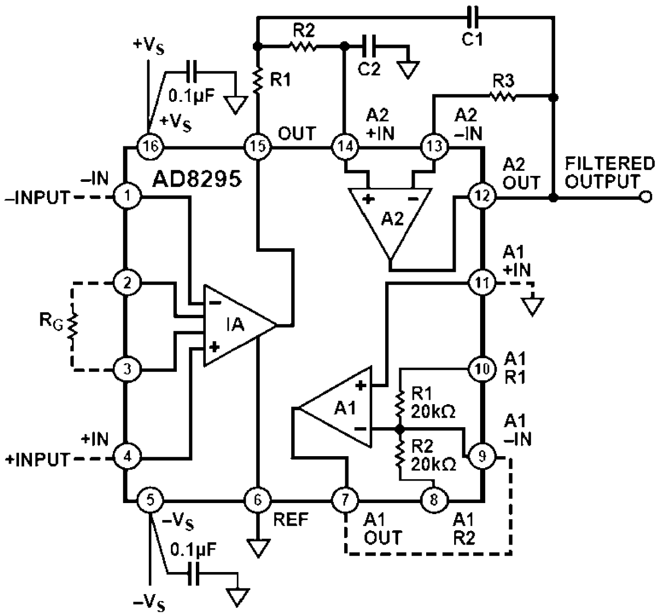

Fig. 2. The schematic of the EMG amplifier circuit that is used in the application

and interelectrode distance of 20 mm. The real sEMG data was converted to digital data with help of a data acquisition card (I/O Tech Comp.) at 16 bits resolution with sampling frequency of 2000 Hz. A recorded sample signal measured over Brachioradialis muscle is shown in Fig. 3(a).

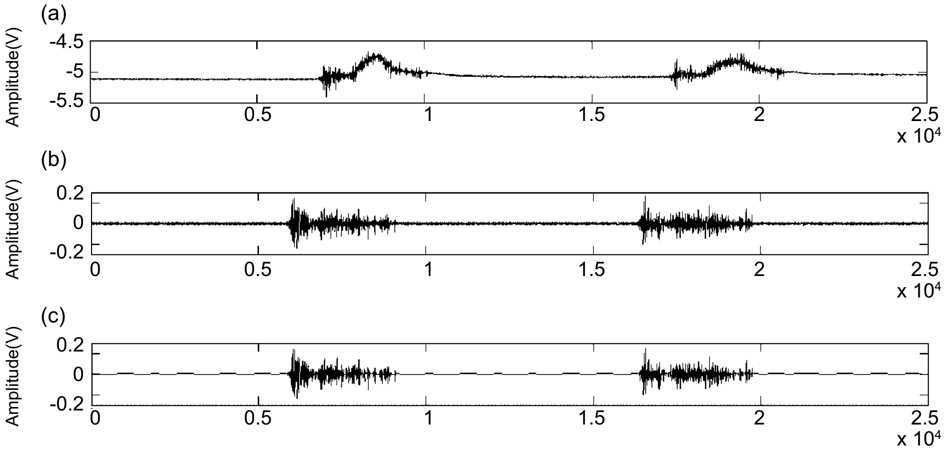

Fig. 3. (a) The sEMG signal recorded over Brachioradialis muscle during cylindrical grasp; (b) High-pass filtered state of the signal in Figure 3(a); (c) Denoised version of the signal in Figure 3(b) with bior1.1 wavelet at eight level

Before placing the electrodes, the subject's skin was cleaned with 70% alcohol swab to remove any oil or dust from the skin surface.

During the recordings the subjects were asked to perform seven different movements namely, hand open, hand close, spherical grasp, cylindrical grasp, precision hold, wrist supination and wrist pronation and each movement was repeated 20 times. A suitable resting time (5 min.) was given between recordings.

2.1. Front-end Processing

The front-end processing is a preprocessing step aimed at preparing of the data for feature extraction and classification. As a first step of the preprocessing, the sEMG signal is passed through high-pass filter with cut-off frequency of 20 Hz to remove Direct Current (DC) component from the measured signal (Fig. 3(b)). The second step is the denoising process. There are several modern methods for denoising of biomedical signals such as wavelet based denoising and EMD based denoising. The wavelet based denoising was chosen in this study because it provides a more robust solution.

The wavelet denoising algorithm is an advanced signal processing method and it has drawn considerable amount of attention in removal of noise from continuous signals like sEMG signals [16, 17]. In the wavelet based denoising three parameters play important role. These parameters are wavelet type (haar, symlet, bior etc.), threshold selection rule (universal, SURE, minimax, hybrid) and threshold method (hard, soft).

So, in order to determine which wavelet type, threshold selection rule and threshold method gives better results in the sEMG denoising process, following study was performed. 0 dB white Gaussian noise was added to a synthetic sEMG signal in MATLAB. Then all combination of forty different wavelet types, four threshold selection rules and two threshold methods were applied to the noisy signal and the parameters that gave the best SNR (Signal-to-noise ratio) values were recorded. In order to verify the results the 0 dB white Gaussian noise was thirty times randomly added to the signal and the same process repeated. The results showed that the bior1.1 wavelet, the SURE threshold selection rule and the hard threshold method gave the best values (Fig. 4). The synthetic sEMG signal, the 0 db white Gaussian noise added signal and the synthetic sEMG signal denoised with the wavelet based technique are shown in Fig. 5(a), 5(b)

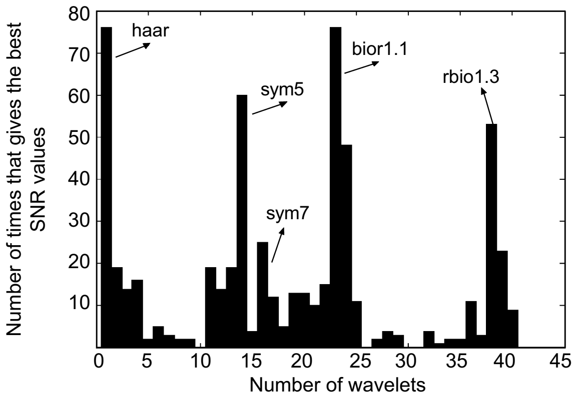

Fig. 4. The histogram of wavelets whose SNR's are above 8 dB at eighth level decomposition

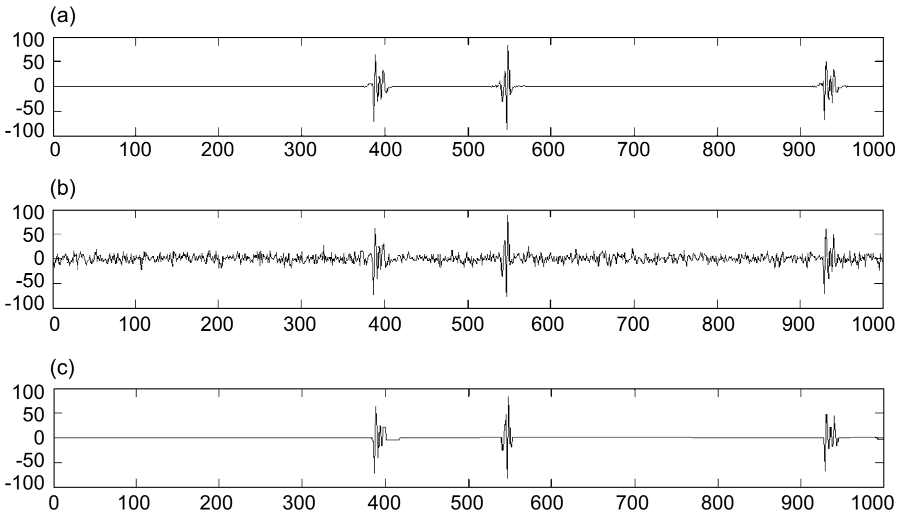

Fig. 5. (a) Synthetic sEMG signal; **(b)** 0 db white Gaussian noise added synthetic signal in MATLAB; **(c)** Denoised Synthetic sEMG signal with wavelet based technique at eighth level decomposition using bior1.1 wavelet type, SURE threshold selection rule and hard threshold type

and 5(c), respectively. In this study, we also used the wavelet based denoising technique. In the denoising process, the recorded signals were filtered with the bior 1.1 wavelet at eighth level by choosing the SURE threshold selection rule and the hard threshold method (Fig. 3(c)). For the last step of the preprocessing, each of the movements was separated for the GMM and the ANN training.

2.2. Feature Extraction

Any classifier's performance is based on numerous factors. One of such factors is the most appropriate choice of the feature set. The way in which we represent the sEMG signals for classification is very important. Generally there are two major approaches, namely, temporal approach and spectral approach to extracting of a feature. The methods used to extract a feature in this study were as follows: Mean Absolute Value(MAV), Willison Amplitude(WAMP), Zero Crossing(ZC), variance(VAR), Slope Sign Changes(SSC), Waveform Length(WL), Simple Square Integral(SSI), Amplitude of First Burst(AFB), Mean Frequency(MF) and Median Frequency(MDF) [16, 18]

2.3. Classification

In the study, an unsupervised learning and a supervised learning based classification methods were used. As the unsupervised based classification method the GMM, and as the supervised one ANN were chosen due to their higher classification rates in the sEMG signals.

2.3.1. Neural Networks

Artificial Neural Networks (ANNs) are non-linear mapping structures based on the function of the human brain. They are powerful tools for modeling, especially when the underlying data relationship is unknown.

The designed ANN consist of three layers: input layer, hidden layer and output layer. The used feedforward backpropagation ANN architecture is shown in Fig. 6. ANN has 40 neurons at the input layer and 7 neurons at the output layer and we tested three different numbers of the hidden neurons (10, 20 and 30). Activation functions of the hidden layer and the output layer were selected as tansig and purelin separately.

The signals, which were taken from four people during seven different hand movements from four channels, were processed for training and validation of ANN. For each channel 10 features were extracted. In the training session 70% (392 data set) of the processed signals was used and remaining 30% of the signals were used for testing of ANN.

Training of ANN was realized by updating weight and bias values according to the Levenberg-Marquardt optimization algorithm [19] and gradient descent was used as the learning function.

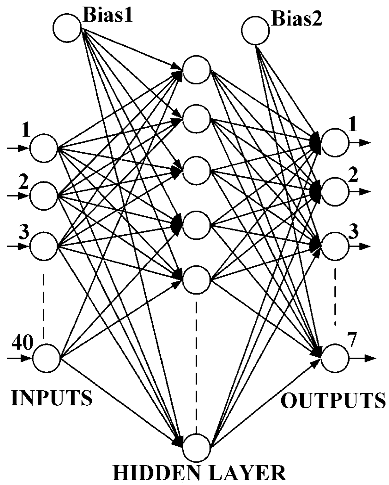

Fig. 6. The Feedforward Backpropagation ANN architecture

2.3.2. Gaussian Mixture Model

Gaussian Mixture Models (GMMs) are one of the well-known statistical methods for clustering. Gaussian mixture density is a weighted sum of M component densities.

$$p(x \mid \lambda) = \sum_{i=1}^{M} \omega_i g(x \mid \mu_i, \Sigma_i) . \tag{1}$$

A GMM model with M component is represented as in equation 1. Where, x is continuous data vector (measurements or features) with D dimension, ω_i, are the mixture weights and $g(x \mid \mu_i, \Sigma_i)$ ($i = 1,\ldots M$) are component densities. The complete Gaussian mixture density is parameterized by the mixture weights, the mean vectors and the covariance matrices. D-dimensional Gaussian component distribution with mean μ and covariance matrix Σ is expressed as equation 2.

$$g(x \mid \mu_i, \Sigma_i) = \frac{1}{(2\pi)^{D/2} \left|\Sigma_i\right|^{1/2}} \exp\left\{ -\frac{1}{2}(x-\mu_i)' \Sigma_i^{-1} (x-\mu_i) \right\} . \tag{2}$$

Expectation Maximization (EM) algorithm provides a good solution for finding the right mixture-density parameters [20]. Also, in this study the EM algorithm was used for finding the GMM parameters.

The GMM-based motion classification system, which is used in the study, is shown in Fig. 7.

For the motion classification, each motion is represented by a GMM and is referred to by its model λ as shown in Fig. 7. There are seven GMM models in the system because of seven different motion are classified. The Gaussian mixture density

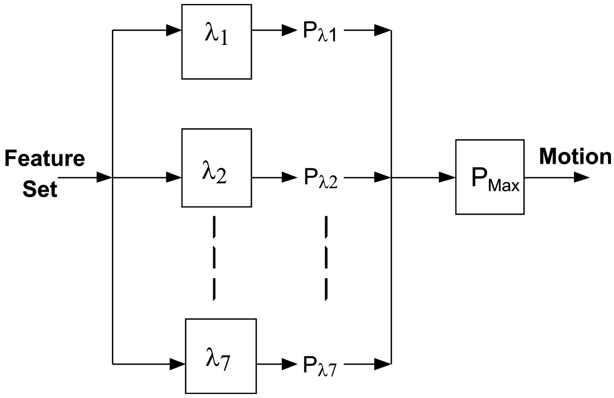

Fig. 7. The GMM-based motion classification system

for each GMM is $P_{\lambda 1}$, $P_{\lambda 2}$…, $P_{\lambda 6}$. The objective is to find the motion class which has the maximum a posteriori probability Pmax for a given feature set. For the training of the GMM the same features were used as for the ANN classification but in the GMM the features were normalized between 0-1. While getting the features, a non-overlapping technique was used.

3. Results

In order to test the classifiers, the training process was repeated 10 times using all extracted features and the mean values of the classification results were calculated. The results for the classification rates of the ANN and the GMM classifiers and the classification rates of each motion are shown in Table 1 and 2 separately.

The best, the worst and the average classification rates of the classifiers are shown in Table 1. According to Table 1, the ANN classifiers gave better rates than the GMM classifier and the network that had 20 hidden neurons showed the highest performance with a 91.95% average classification rate compared to the others.

In Table 2, the classification results are given according to the motion when all extracted features were used. The indicated motions are ordered as follows hand open, wrist pronation, precision hold, wrist supination, spherical grasp, cylindrical grasp and hand close. It can be seen from Table 2 that motions 1 (hand open) and 7(hand close) had the highest classification rates in the ANN and the GMM classifiers. ANN classified motions 2 (wrist pronation) and 5 (spherical grasp) with the lowest percentage, and the GMM had classified motions 4(wrist supination) and 5 with the lowest percentage.

Using a vector consisted of less features is very important in real time application so in order to determine how the feature vectors affect the classification performance

Table 1. Classification rates of ANN and GMM

Classifier	Test Accuracy (Percentage)			Number of Hidden Neurons
	Max.	Min.	Average	
ANN	92.85	81.6	86.66	10
	95.42	85.71	91.95	20
	94.89	83.45	89.26	30
GMM	83.05	73	80.33	–

Table 2. Classification rates of each motion

	Motion	Classification Rate(Percentage)			Hidden Neurons
		Maximum	Minimum	Average	
Neural Network Classifier	1	100.00	82.14	94.64	**10**
	2	89.30	67.85	77.90	
	3	96.40	71.42	86.20	
	4	100.00	67.85	88.07	
	5	100.00	75.00	87.50	
	6	96.40	71.40	85.70	
	7	96.40	82.14	93.42	
	1	100	89.28	96.42	**20**
	2	100	75	86.89	
	3	100	85.71	94.03	
	4	96.42	85.71	91.64	
	5	96.42	75	86.89	
	6	100	85.71	92.85	
	7	96.42	82.14	92.25	
	1	100	89.28	94.64	**30**
	2	92.85	71.4	80.92	
	3	96.42	71.4	87.50	
	4	92.85	75	85.71	
	5	96.42	75	88.67	
	6	96.42	67.85	88.07	
	7	100	64.28	88.07	
GMM Classifier	1	85.71	66.67	82.85	----
	2	85.71	52.38	82.14	
	3	85.71	52.38	80.9	
	4	80.95	66.67	76.28	
	5	71.43	38.10	68.45	
	6	80.95	47.62	79.56	
	7	95.24	61.90	90.47	

of the ANN and the GMM classifiers the following study was performed. Using the same ANN model in Fig. 6 with 20 hidden neurons and the GMM model in Fig. 7, the classifiers were trained 10 times and the results were recorded. During the training, the individual feature vectors and their combinations were used instead of using all feature vectors. The results are shown in Table 3 and Table 4.

According to Table 3, the SSC feature vector had the highest performance with 68.26% classification performance in ANN and 59.18% classification performance

Table 3. Classification rates of individual features

Feature Numbers	Feature Names	ANN Classification Rates(%)			GMM Classification Rates (%)		
		Maximum	Minimum	Average	Maximum	Minimum	Average
1	MAV	69.86	56.63	63.87	54.86	40.24	48.29
2	WAMP	70.09	61.22	65.01	61.57	48.43	54.10
3	ZC	68.36	52.04	63.31	64.27	51.49	59.08
4	VAR	60.71	42.85	55.10	47.24	35.48	40.14
5	SSC	73.46	60.71	68.26	66.85	50.18	59.18
6	WL	72.95	61.73	66.58	61.23	47.56	55.78
7	SSI	62.48	48.46	55.51	37.45	27.36	30.61
8	AFB	62.75	52.00	57.40	44.34	31.42	38.78
9	MF	72.00	62.24	66.99	65.87	45.86	55.10
10	MDF	66.80	57.65	61.37	58.96	43.27	53.06

Table 4. Average classification rates of ANN and GMM classifiers according to features

Feature Numbers	Feature Names		Features	Average Classification Rates (Percentage)	
				ANN	GMM
			1,2,10	91.1	66.7
1	MAV		1,2,6	91.1	78.94
2	WAMP		1,2,3,6	91.24	71.46
3	ZC		1,2,3,5,6	93.72	78.94
4	VAR		1,2,3,4,5,6	93.87	76.22
5	SSC		1,2,3,4,5,6,9	94.23	80.33
6	WL		1,2,3,4,5,6,10	93.57	83.7
7	SSI		1,2,3,4,5,6,9,10	94.08	84.38
8	AFB		5,9	83.57	76.57
9	MF		5,6,9	91.27	74.14
10	MDF		2,5,6,9	93.36	81.42

in the GMM respectively. Other feature vectors that provide high classification rates were MF, WL, WAMP and ZC. The feature vectors that performed the lowest classification rates were VAR, SSI and AFB.

In Table 4, the averages of classification performances for the combination of the selected feature vectors are shown. In the study, 11 different combinations of the feature vectors were tested.

As can be seen from Table 4, the classification rates of the ANN and the GMM based classifiers' performances were increasing with the number of the feature vectors' but it did not provided any significant advance in the classifiers' performances especially for the ANN classifier. Also this study showed that the used frequency domain features increase the GMM classifiers' performance more than the ANN classifiers'.

4. Conclusion

In this paper, firstly, it was investigated which type of wavelet, threshold selection rule and threshold method would provide the best result for denoising of the sEMG signals. This study also illustrated that the bior1.1 wavelet type, the SURE threshold selection rule and the hard threshold method provided the best SNR values on the synthetic signal.

The classifications of seven hand motions were realized with the ANN and the GMM classifiers using the sEMG signals. In this study, the feedforward backpropagation ANN was used and it was tested separately for the different numbers of hidden neurons (10, 20 and 30). The experimental results showed that the ANN classifiers outperformed the GMM classifiers and the network with 20 hidden neurons gave better results when compared to others. During the training of classifiers, 10 different feature vectors were used.

In the previous studies [21, 22], the effects of feature vectors were not added to the papers. In our study, the effects of the extracted individual feature vectors and the combination of the feature vectors were investigated based on the classification of the hand motions. According to our study, the individual feature vectors did not exhibit the right capability to classify the right motion for applications. The SSC feature vector had the highest classification rates of 68.26% and 59.18% using the ANN and the GMM classifiers, respectively. Besides this, a combination of three or four feature vectors, instead of using all feature vectors, delivered enough data for getting the high classification rates. Our study showed that the feature vectors 2(WAMP), 5(SSC), 6(WL) and 9(MF) can classify the motions with 93.36% and 81.42% accuracy using the ANN and the GMM classifiers, respectively.

Furthermore, the classification performances were examined according to the motion. The results showed that motion 1(hand open) and motion 7(hand close) had the highest classification rates both in the ANN and the GMM based classification.

While, motion 2 (wrist pronation) had the lowest classification rates in the ANN based classification, motion 4 (wrist supination) had the lowest classification rates in the GMM based classification. Their classification rates could be increased by using extra electrode or placing electrodes on the extensor muscles.

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