A Novel Prosthetic Hand Control Approach Based on Genetic Algorithm and Wavelet Packet Transform Features

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***Abstract*— This paper presents a novel approach to optimize pattern recognition system using genetic algorithm (GA) to identify the type of hand motion employing artificial neural networks (ANNs) with high performance and accuracy suited for practical implementations. To achieve this approach, electromyographic (EMG) signals were obtained from sixteen locations on the forearm of six subjects in ten hand motion classes. In the first step of feature extraction of forearm EMG signals, WPT is utilized to generate a wavelet decomposition tree from which WPT coefficients are extracted. In the second step, standard deviation of wavelet packet coefficients of EMG signals is considered as the feature vector for training purposes of the ANN. To improve the algorithm, GA was employed to optimize the algorithm in such a way that to determine the best values for ''mother wavelet function'', ''decomposition level of wavelet packet analysis'', and ''number of neurons in hidden layer'' concluded in a high-speed, precise two-layer ANN with a particularly small-sized structure. This proposed network with a small size can recognize ten hand motions with recognition accuracy of over 98% and also resulted in improvement of stability and reliability of the system for practical considerations.**

***Index Terms*—Electromyographic (EMG) signal, Feature extraction, Pattern recognition, genetic algorithm, wavelet packet transform**

I. NTRODUCTION

THE The electromyographic signal (EMG), measured at the surface of the skin, provides valuable information about the neuromuscular activity of a muscle and this has been essential to its application in clinical diagnosis, and as a source for controlling assistive devices, and schemes for functional electrical stimulation[1],[2]. Its application to control prosthetic limbs has also presented a great challenge, due to the complexity of the EMG signals. An important requirement in this area is to accurately classify different EMG patterns for controlling a prosthetic device. For this reason, effective feature extraction is a crucial step to improve the accuracy of pattern classification, therefore many signal representations have been suggested. Various temporal and spectral approaches have been applied to extract features from these signals[1],[5],[6]. A comparison of some effective temporal and spectral approaches is given in[7], where the authors have applied moments to short time Fourier transform (STFT)[5], and short time Thompson transform (STTT)[8].The later transform has shown the best performance in case of short temporal sequences. The wavelet transform-based feature extraction techniques have also been successfully applied with promising results in EMG pattern recognition [3],[4].The discrete wavelet transform (DWT) and its generalization, the wavelet packet transform (WPT), were elaborated in[3].These techniques have shown better performance than the others in this area because of its multilevel decomposition with variable trade-off in time and frequency resolution. The WPT generates a full decomposition tree in the transform space in which different wavelet bases can be considered to represent the signal. The techniques were applied to feature extraction from surface EMG signals.

Park & Lee [9] presented a fuzzy-based decision-making system to classify six motions of the six subjects, including elbow flexion and extension, wrist pronation and supination, and in and out humeral rotation. Hudgins et al. [4] compared frequency domain and time–frequency methods to preprocess EMG signals and introduced wavelet packet transform with satisfactory results. Parker et al. [10] applied the combination of wavelet packet and principal component analysis to extract suitable features from myoelectric signals to classify six classes of hand motions. Englehart et al. [11] also developed a wavelet-based system to control myoelectric signals of four classes of hand motions with high accuracy, low response time, and a user interface control system in 2003. Lowery et al. [12] presented a finite element method (FEM) model to investigate the effect of skin, muscle, fat, and bone tissue on simulated surface electromyographic (EMG) signals and demonstrated that all aforementioned materials have an effect on EMG signals. Gazzoni et al. [13] proposed an ANN-based automatic detection and identification system to pinpoint motor unit action potentials using wavelet transform and artificial neural network in specific case studies. Sebelius et al. [14] introduced an ANN-based intelligent system to classify seven hand movements for limited subjects.

In this research, we propose a novel approach to recognize ten hand motions based on EMG signals using WPT to extract the feature vector from sixteen channels. then, standard deviation of WPT coefficients as feature vectors are constructed and finally, a multilayer perceptron(MLP) is used to classifies feature vector into ten hand motions. To achieve a high recognition accuracy for multifunction myoelectric hand control, GA is employed to optimize best values for "mother wavelet function", "decomposition level

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of wavelet packet transform" and "number of neurons in hidden layer".

II.SURFACE AND INTRAMUSCULAR EMG SIGNALS

In this research, both measures of forearm EMG signals have been collected and processed, although the major goal is surface EMG signal analysis, which is applicable to prosthetics. Two different data acquisition systems were used to collect surface and intramuscular EMG signals [15]. For surface EMG signals, a 16-electrode linear array with interelectrode spacing of 2 cm was used (see Fig.1). Each channel was filtered between 10 and 500 Hz and amplified with a gain of two thousand. Frequency information of surface EMG is shown in Fig. 2 for one subject using power spectrum density (PSD). For intramuscular EMG, needles were implanted in the pronator and supinator teres, flexor digitorum sublimas, extensor digitorum communis, and flexor and extensor carpi ulnaris.

These measures were used to record time-domain signals regarding grip, wrist flexion and rotation, and gross movement[16]. These six channels of data were also filtered and amplified (see Fig. 1). These were recorded in six subjects while they performed the ten hand movements for 5 s each, with a 2 min resting period after each exercise. The tests were repeated for each subject, resulting in 10 s of EMG signals per person for each motion. The subjects denied feeling fatigued during these exercises. After recording EMG signals by means of sixteen electrodes for surface and six electrodes for intramuscular EMG, the raw signals were segmented into the 256-point windows [15] as shown in Fig. 4 for surface EMG signals.

The studied hand motions include forearm pronation (FP), forearm supination (FS),wrist flexion (WF), wrist extension (WE), wrist abduction (WAB),wrist adduction (WAD), key grip (KG), chuck grip (CG), spread fingers(SF), and a rest state (RS).

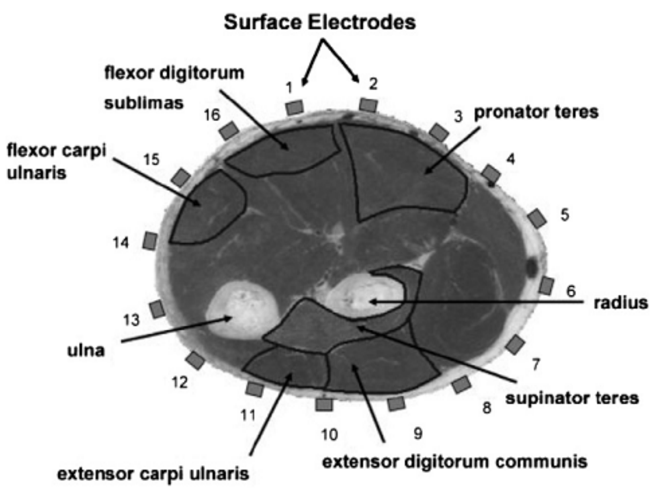

Fig.1 A cross section of the upper forearm to illustrate the location of 16 surface electrodes and six needle electrodes.

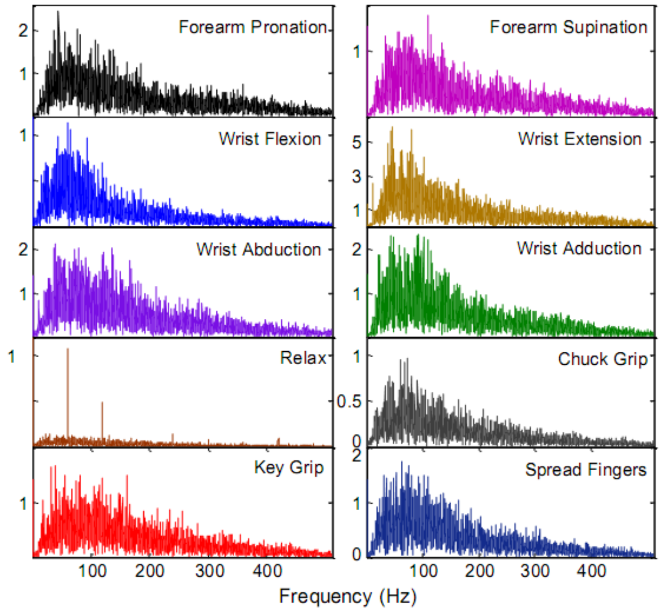

Fig.2 Power Spectrum Density(PSD) of surface EMG signals of ten hand motions recorded from one of the channels of the data acquisition system

III.WAVELET TRANSFORM AND FEATURE SELECTION

A. Wavelet Transform

Fourier analysis has the serious drawback that transitory information is lost in the frequency domain. This may be alleviated in the use of a short-time Fourier Transform (STFT),but when a time window is chosen, that window is the same for all frequencies of the signal being analysed, causing possibly essential information to be lost at very low or high frequencies. The essential advantage of the wavelet transform over Fourier transform or STFT is that the time-frequency window is flexible and adapts in such a way that there is always about the same number of periods of the frequency analysed in the time window [3]. Wavelet analysis allows the use of long time-intervals for more precise low frequency information, and shorter regions for more high frequency information.

The wavelet transformation is achieved by the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. Wavelets are able to determine if a quick transitory signal exists, and if so, can localise it. This feature makes wavelets very useful for the study of the EMG waveforms[10].

The wavelet packet analysis [17] is an expansion of classical wavelet decomposition that presents more possibilities for signal processing. In wavelet transform, signals split into a detail and an approximation. The approximation obtained from first-level is split into new detail and approximation and this process is repeated. Because of the fact that WT decomposes only the approximations of the signal, it may cause problems while applying WT into certain applications where the important information is located in higher frequency components. The main difference between WT and WPT is that not only approximations but also details are decomposed in WPT. Thus, with the use of WPT, a better frequency resolution can be obtained for the decomposed signal. In addition, the use of WPT extracts much more

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features about the signal. For the n-level decomposition, the raw segmented signal is split as show in Fig. 3.

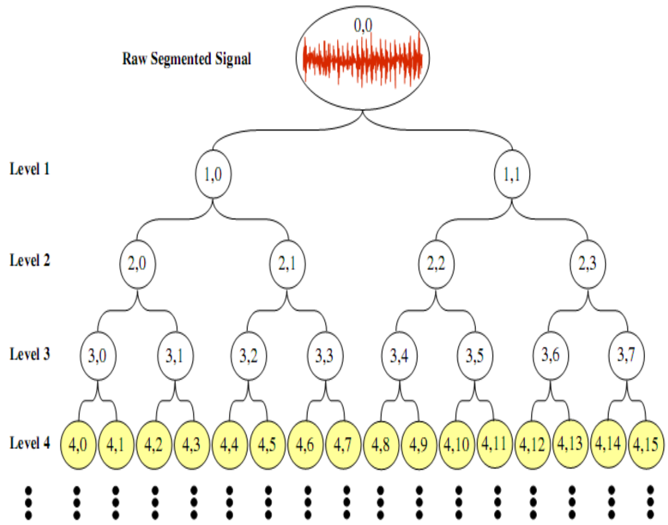

Fig.3 Decomposition tree and the level of decomposition

In this research, wavelet packet has been used to pre-process the signals. A wavelet packet is a function with three indices of integers i, j and k which are the modulation, scale and translation parameters, respectively,

$$\Psi^{i}_{j,k}(t) = 2^{j/2}\,\Psi^{j}(2^{j}t - k),\; i = 1,2,3,\ldots \quad (1)$$

The wavelet functions Ψ^{j} are determined from the following recursive equations:

$$\Psi^{2j}(t) = \sqrt{2}\sum_{-\infty}^{\infty} h(k)\,\Psi^{i}(2t-k) \quad (2)$$

$$\Psi^{2j+1}(t) = \sqrt{2}\sum_{-\infty}^{\infty} g(k)\,\Psi^{i}(2t-k) \quad (3)$$

The original signal $f(t)$ after j level of decomposition are defined as follows:

$$f(t) = \sum_{i=1}^{2j} f^{i}_{j}(t) \quad (4)$$

while the wavelet packet component signal $f^{i}_{j}(t)$ are stated by a linear combination of wavelet packet functions $\Psi^{i}_{j,k}(t)$ as follows:

$$f^{i}_{j}(t) = \sum_{k=-\infty}^{\infty} c^{i}_{j,k}(t)\,\Psi^{i}_{j,k}(t) \quad (5)$$

where the wavelet packet coefficients $c^{i}_{j,k}(t)$ are calculated by:

$$c^{i}_{j,k}(t) = \int_{-\infty}^{\infty} f(t)\,\Psi^{i}_{j,k}(t)\,dt \quad (6)$$

providing that the wavelet packet functions satisfy the orthogonality:

$$\Psi^{m}_{j,k}(t)\Psi^{n}_{j,k}(t) = 0 \text{ if } m \neq n \quad (7)$$

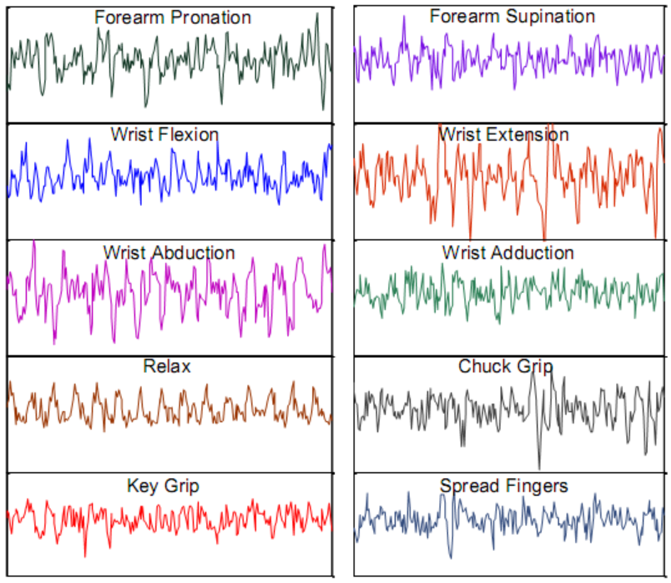

Fig.4 Segmented surface EMG in a 256 points window from one subject performing 10 hand motions

B. Feature Selection

The most common technique used to identify the motions of myoelectric hand is energy of wavelet coefficients as the feature vector to train the neural networks. In this paper, a new feature vector is suggested which utilizes standard deviation rather than the energy levels of wavelet coefficients and is employed to train the neural network to recognize the ten hand motions. Standard deviation is a widely used measurement of variability or diversity used in statistics and probability theory. It shows how much variation or dispersion there is from the average (mean). A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data is spread out over a large range of values. Technically, the standard deviation of a statistical population, data set, or probability distribution is the square root of its variance. A useful property of standard deviation is that, unlike variance, it is expressed in the same units as the data. Note, however, that for measurements with percentage as unit, the standard deviation will have percentage_points as unit. There are two common textbook definitions for the standard deviation S of a data vector :

$$S = \left(1/(n-1)\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{1/2} \quad (8)$$

$$S = \left(1/(n)\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{1/2} \quad (9)$$

where

$$\bar{x} = (1/n)\sum_{i=1}^{n} x_i \quad (10)$$

and n is the number of elements in the sample. The two forms of the equation differ only in $(n-1)$ versus n in the divisor. The results show that the suggested method augments

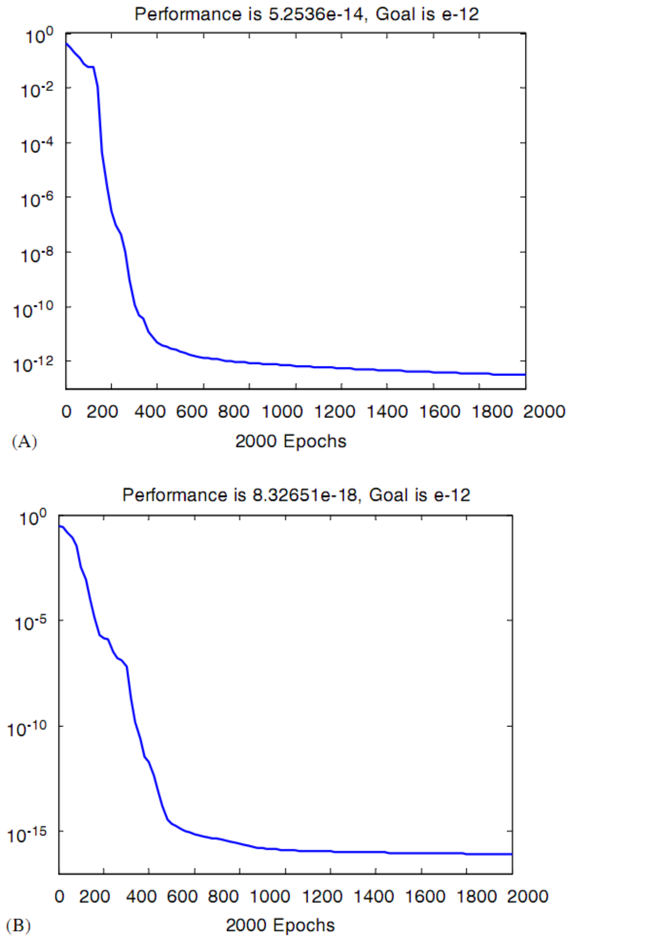

Fig. 5. Network performance for: (A) energy levels, and (B) standard deviation of wavelet coefficients as feature vector.

convergence and performance of the network considerably. Fig. 5(A) and (B) show the training performance for energy and standard deviation of wavelet coefficients, respectively, showing the superior performance of standard deviation method.

IV. ARTIFICIAL NEURAL NETWORK

Artificial neural networks which are also called parallel distributed-processing systems or connectionist systems are made of simple processing units, called neurons [18] capable of storing experimental knowledge as a natural propensity, have a variety of architectures, remarkable of which are the feedforward and recurrent networks. The most popular neural network is the multi-layer perceptron, which is a feedforward network and frequently exploited in pattern recognition systems. Among all architectures, the multi-layer feedforward networks trained with Back Propagation (BP) algorithm seems to be the most significant and widely used method in pattern recognition of prosthetic hand motions.

Fig. 6 shows schematically the utilized ANN structure used in this research. An important network design issue is the selection and implementation of the network configuration. In general, a two-layer MLP made up of an input layer, a hidden layer, and an output layer which is the smallest achievable structure is applied to reduce the developing expense of the hand motion identification neural network, while maintaining the desired level of accuracy and robustness of the motion recognition. Hyperbolic tangent sigmoid transfer function was applied to all net layers with Back propagation training algorithm [20].The output layer contains 10 neurons which represent 10 hand motions. For MLP, the initial values of the weights and bias are the same for different algorithms, the error goal of the network learning is 10^{-12}, learning rate is 0.05 and performance function is MSE (Mean Squared Error).

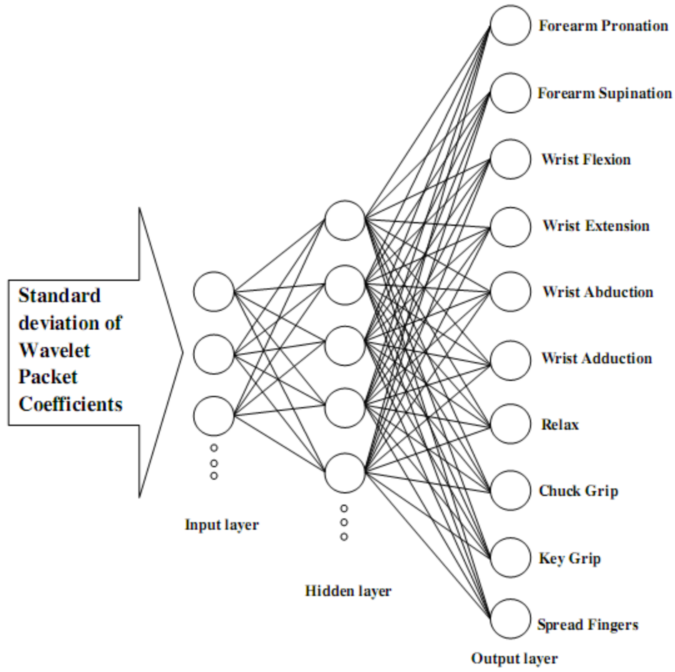

Fig.6 Schematic diagram of MLP network

V. GENETIC ALGORITHM

Genetic algorithm (GA) is a kind of search and optimization algorithm that have been produced from simulating biologic heredities and long evolutionary process of creatures. It stimulates the mechanism of “survival competitions”; the superior survive while the inferior are eliminated, the fittest survive. The mechanism searches after the optimal subject by means of a successive iterative algorithm. Ever since the late 80s, GA, as a new cross discipline which has drawn people’s attention, has already shown its increasing vitality in many fields [20].

First, we should determine a genetic encoding scheme, there are several ways to encode a chromosome; for example, Binary encoding, Real encoding and Order encoding. In this research, binary encoding is our choice. In binary encoding, GA applies strings of binary bits (1s and 0s) representing chromosomes to describe multiple points in the search space of the problem domain.

Evaluation is performed based on the fitness of the chromosome. The creation of a fitness function to rank the performance of a specific chromosome is of paramount importance for the success of the training process. The genetic algorithm rates its own performance around that of the fitness function; consequently, if the fitness function does not adequately take account of the desired performance features, the genetic algorithm is unable to meet the deserve requirements of the user.

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In this research, Roulette wheel selection scheme has been applied among the selection operators [21].Two-point crossover was used for each chromosome of the chromosome-pair having a 50% chance of selection, the two parents selected for crossover exchange information lying between two randomly generated points within the binary string.

The proposed chromosome includes six genes for Daubechies mother wavelet function, two genes for decomposition level of signals, and five genes pertain to the number of neurons of hidden layer which is depicted in Fig. 7. Furthermore, the following linear equation was used as the fitness function F.

$$F = \alpha . p + \beta . t \quad (11)$$

where α and β are the weights, p and t denote network performance and training time, respectively. In general, the network performance which is directly related to the accuracy of the network outweighs the training time constraint due to the significance of the system accuracy in the hand motion recognition system. Therefore, to optimize the system, network performance has more impact on fitness function than training time; the weights were applied where α was assumed to be 0.9 vs. -0.3 which was assigned to β.As the more training time has the more negative impact on the whole motion identification system, negative sign has been considered for β in fitness function.

To sum up, GA was used to optimally search Daubechies order, decomposition level of the signals, and the number of neurons in hidden layer. Tables 1 and 2 explore, respectively, the parameters and variables of the GA exploited in the research.

VI. RESULTS AND DISCUSSION

In this paper, by using GA, DB44, level 4 and 11 neurons have been chosen as the optimized values for Daubechies order, decomposition level, and the number of nodes in hidden layer, respectively. With close examination of the amplitude of the wavelet packet coefficients, it has been clarified that there is a considerable correlation between DB44 and the motion identification. The values of fluctuations of the standard deviations in different segmented signals for various motions are considerable and this is the most appropriate factor for training the neural networks. Most significantly, the preciseness of discriminating the motions cannot be obtained through other Daubechies except for DB44.By using other Daubechies, distinguishing between the motions is not as easily as DB44 and therefore, classification of motions will be inaccurate. Consequently, Daubechies wavelet function with the order of 44 was selected as the most proper function by GA for motion classification. Although, the network structure is compact in decomposition level of 3 (due to 8-element network input), obviously no satisfactory results were obtained. In spite of the higher performance and better results, the decomposition level of 5 leads to a larger number of neurons of the hidden layer (32-element network input) which leads to the complexity of the system. Therefore, fourth decomposition level was determined to be the most appropriate level for this case study because of the better outcomes than those of the others. In addition, the optimal number of the neurons in the hidden layer was determined using genetic algorithm not only proved the high capabilities of this algorithm in order to find the optimal solution but also verifies the soundness of the parameters for the adjustment of the algorithm presented in Table 1.

Fig.7 Proposed chromosome for GA

TABLE 1
GA PARAMETERS

Number of generations	300
Population	20
Chromosome length	13
Selection operator	Roulette
Fitness normalization	Rank
Elitism	1
Crossover	Pc = 0.8,two-point,uniform
Mutation	Pm = 0.1, Gaussian, mean = 0.0, std = 1.0

TABLE 2
GA VARIABLES

Variable name	Range	Optimized value
Daubechies order	DB2-DB45	DB44
Decomposition level	3-6	4
Number of the hidden-layer neurons	7-25	11

VII. CONCLUSION

An intelligent pattern recognition system was developed and implemented to examine the hand motions; Three parameters were recognized to be of most significant to be optimized using GA i.e. Daubechies wavelet function order, decomposition level, and number of neurons in hidden layer of ANN, which play a key role in size and performance of the network and the soundness of the feature vector. The Feature vector was also obtained from optimized standard deviation of wavelet packet coefficients acquired from DB44 at fourth level of decomposition. Eventually, a MLP network with well formed and optimized structure (16:11:10) and remarkable accuracy over of 98% was presented providing the capability to identify ten hand motions include forearm pronation (FP), forearm supination (FS),wrist flexion (WF), wrist extension (WE), wrist abduction (WAB),wrist adduction (WAD), key grip (KG), chuck grip (CG), spread fingers(SF), and a rest state (RS) .

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