Strong/Weak Muscle Fiber Analysis by Pattern Recognition of SEMG Based On BP and RBF Neural N/W

Guropinder Singh, Parvinder Singh

Abstract: In this paper, we use both BP neural network and RBF neural network to identify SEMG from human upper arm (Bicep). In the experiments, we study the SEMG signal strength by different algorithm We use two electrodes to extract SEMG signal from the upper arm biceps, then analyze this signal using the peak value of SEMG signal , put this value vectors into BP neural network and RBF neural network to complete strength recognition. The results of the experiments using the method introduced in this paper show that the average recognition rate of strength of muscle are above 94 % for BP and is above 99% for RBF neural network.

Keywords- BP neural network; pattern recognition; RBF neural network; Surface Electromyography Signal.

I. INTRODUCTION

SEMG is the biological signal produced by neuromuscular activity and taken by electrodes from the surface of human skeletal muscle, it reflects the neuromuscular activity to some extent, so the value of the SEMG can be used to distinguish the various body movements and strength. It is researched in clinical medicine, sports medicine, biological medicine and engineering and many other areas of extensive field research at at present[1]. People's identification of the SEMG has been made some progress after years of development. In paper[2], Yuqing make use of four SEMG signals and BP neural network, 8 gestures are identified and the average recognition rate is over 90%, but it didn't break down the arm movements and accomplish multilevel action identification. In paper [3] six different arm movements recognition according to the feature vectors of SEMG taken from biceps and triceps, the average recognition rate of BP is over 90%. In paper[4],It is studied that range of SEMG signal vary from few micro volts to 20 mili volts. [5] In This it can be seen on RBF neural network for the muscle motion has total recognition rate is over 90% and accuracy rate of the RBF neural network is higher. RBF network is the three-lever former neural networks based on Partial Approaches. Any input and output data of the value of networks should be adjusted in traditional ways of the overall neural network. But in a local approximating neural network there is only few weight of RBF Neural Network influencing the output of the network. So the learning speed of RBF Network is much faster. Because RBF neural network has simple structure, fast training process, and a good non-linear feature, it is widely used in the areas of signal processing and pattern recognition.

II. METHOD OF SEMG PROCESSING

The SEMG is regarded as a variance with Gaussian distribution having the zero mean in the traditional way. In fact, the standard deviation of EMG stands for the value of EMG and reflects the strength of muscle contraction. So we can produce different control signals on the basis of the value of 2 σ. The process is shown in Figure 1.

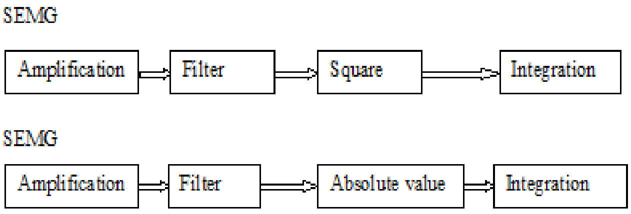

Fig.1 Traditional process

III. BP NEURAL NETWORK CLASSIFIER

BP neural network is a multi-layered feed-forward network, proposed by the PDP group of the California University in 1986,named BP neural network because it's learning mechanism is error back propagation algorithm. BP neural network is widely used in all the artificial neural network with a strong capacity of pattern classification [6],which consists of input layer, output layer and one or more hidden layer. The nodes or neurons interconnected to each other make up the network. In the BP neural network, the neurons between the left and right layers are connected fully, but the upper and lower neurons don't have any connection. When a learning mode is set to the network, the neuron activation values from the input layer spread to the output layer through the hidden layer. In the output layer output of the neural network output the response corresponding to the input mode and then amend the connection weights from the output layer to input layer through hidden layer in order to reduce the error between the desired output and the actual output. Because of this weight correction process is carried out from the output to input layer, so is called "error back propagation algorithm".

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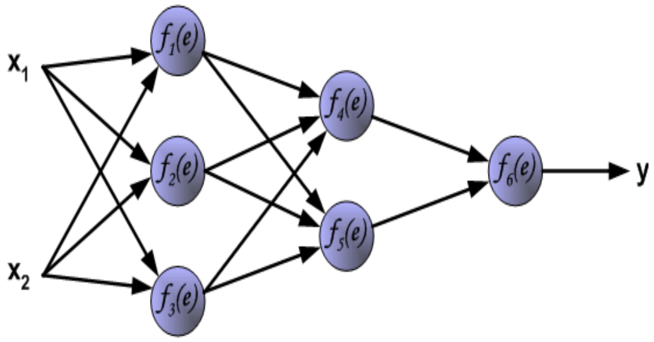

Figure 2: The structure of BP neural network

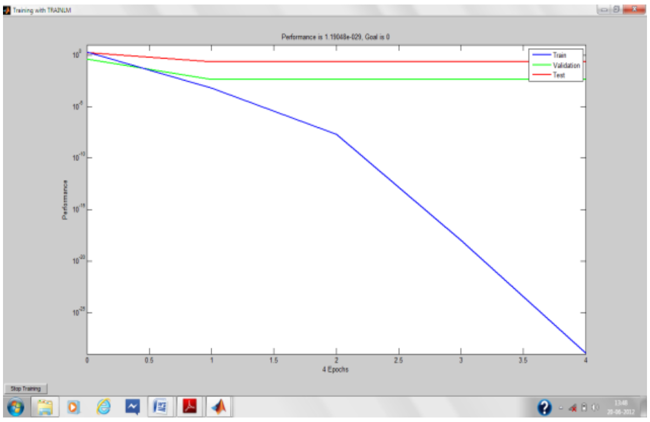

Figure 3 BP neural network's training process

In the signal system and pattern recognition field, BP neural network is a widely used model, the network's structure as shown in Figure 2.In the experiment, we choose three layers structure of BP neural network as classifier. The number of input layer's neuron node is 8, The number of output layer's neuron node is 3.The theory of neuron node's selecting for hidden layer is still not mature, the general method for it's selecting is by experiments. The number of neuron node for hidden layer is set 10 in this article. we extracted surface EMG signals from arm biceps of four different person having different age(male) and having different strength like very weak, weak ,strong and very strong ranging between few microvolts to 20 milivolt .we study the peak value of every SEMG signal of different person, use this value as input to our BP neural network with the 3 neuron node's output in output layer. Set training objectives error 0.01,BP neural network's training process shown in Figure 3.

IV. THEORY OF RFB NEURAL NETWORK

RBF neural network is an artificial neural network which uses to local receives and implements function on the basis of biologic local regulation and overlapped domain knowledge [7]. It is a three-lever net: the input layer (formed by the signal source nodes), the hidden layer (transform function of hidden units is the centre of the radial symmetry and attenuation of the non-negative non-linear function) and the output layer (respond to the input mode). RBF network's most important feature is that the middle hidden layer neurons function only responds to the local reaction of importation of residual part. When the imported functions landed a local area in the space, it generates an important non-zero response. In other cases, output function is very little (similar to zero).

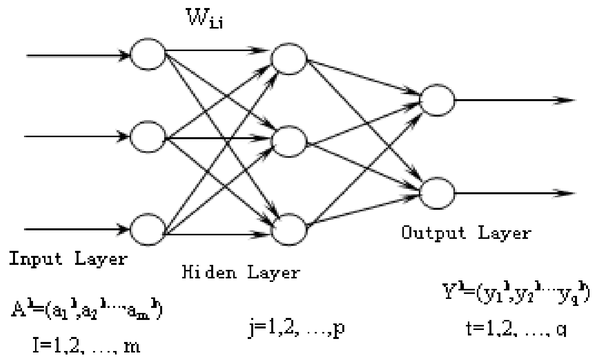

Fig.4 RBF Structure of Network

Fig.4 is a RBF neural network structure. The input layer of network contains m neurons. The hidden layer possesses p(p <m) neurons, where any neuron names i and the i'th hidden Unit output of incentives is "basis function" $i\varphi(x, ti)$. The output has q neurons. The value of Hidden layer and the output layer is *ij w*, using (i = 1, 2, ..., I), (j = 1, 2, ..., J). RBF neurons transform Gaussian function as follows [8].

$$R_j(X) = \exp\left(-\frac{\|X - X_c\|^2}{2\sigma_j^{\ 2}}\right)$$

Where c x is the centre of the kernel function. σ is the width parameter of the function who controls radial range of function. The output of each node is the sum of the output and the weight of the hidden layer neurons y in the RBF neural networks. According to the definition of Gaussian distribution function, hidden layer neurons y in the output and input vector x function should be subjected to the normal distribution. When X closes to the centre vector C, y closes to the maximum. By contrast y is the minimum. If the distance between X and C is wider than σ (that is away from the centre), the output y can be approximately zero. It achieves partial sense. But to RBF network, it completes non-linear mapping from input to the hidden layer. The network output parameters are linear in terms of the adjustable parameters. Thus, we can improve the learning speed and avoid the emergence of the local minimum.

V. EXPERIMENT RESEARCH

The Purpose of the experiments is to use BP and RBF neural network completed through training to identify the strength of surface EMG signals. The EMG signals used in the experiments are extracted from right arm biceps surface of 4 different healthy providers. In this paper, the experimental platform as follows: LABVIEW8.0 software and All data acquisition is done by using the NI USB 6251 and recorded with the MATLAB7.5 software for further processing. In experiment, the two vertical surface electrodes are affixed to the healthy subjects to get the surface EMG. It is a waveform in Figure 5 for a particular muscle, and the signal waveform is enlarged 1000 times. Abscissa signal is the time of the acquisition and longitudinal coordinates is the time series.

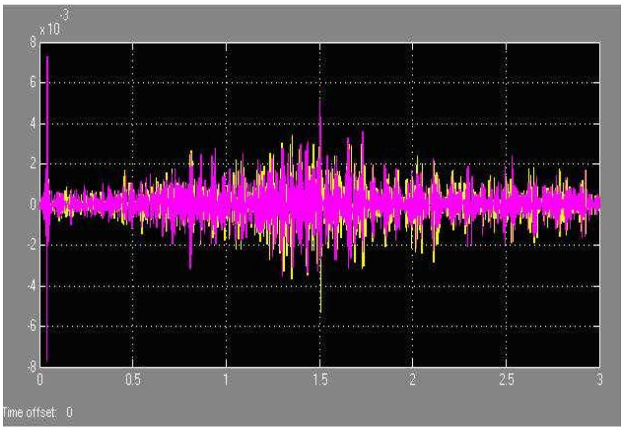

Fig.5 The Signal Of The Surface EMG

We can get real EMG through EMG acquisition circuit. These signals can be filtered and amplified. Data acquisition card may get data that will be dealt with. We study the peak voltage level of SEMG signal taken from data acquisition card. We take advantage of BP network, RBF neural networks to achieve the correct muscle strength recognition rate respectively. We categorised the muscle strength into four different type based on there value in mv, ie very weak muscle fibre, weak muscle fibre, medium muscle fibre and strong muscle fibre. The 72 sets of values of EMG signals correspond to 4 different type of muscle used in experiment foe each BP and RBF network, out of which 54 serve as training class to complete the training for neural network, 18 sets as the test class to check and measure the experimental results. We assume that the sum-squared error goal of the RBF training network is 0.02 in this paper. The results can be seen on RBF neural network for the strength of very weak, weak, medium and strong muscle has total recognition rate is above 99 % in table 3. They are significantly higher than recognition rate for BP neural networks for the strength of very weak, weak, medium and strong muscle. It has total recognition rate is above 94 % table 3. That indicates that accuracy rate of the RBF neural network is higher.

Table I The Identification Results Of Surface Emg Signals For Bp

Type of muscle / Input Signal(mv)	Very weak	Theoretical Value	weak	Theoretical Value	medium	Theoretical Value	strong	Theoretical alue
1	1.0000	1	-0.0013	0	0.4904	0	-0.1459	0
2	0.9910	1	-0.0540	0	-0.0450	0	0.4574	0
3	0.9374	1	-0.0032	0	0.9770	0	0.1534	0
4	1.0859	1	0.0103	0	-0.2988	0	-0.6813	0
5	0.0035	0	0.9948	1	-0.0052	0	-0.1921	0
6	0.0040	0	0.9972	1	0.0642	0	-0.1379	0
7	0.2971	0	0.0070	0	0.9109	1	-0.0093	0
8	0.2315	0	-0.3663	0	1.4129	1	0.3413	0
9	-0.5668	0	0.0017	0	0.2375	1	0.0023	0
10	-0.0112	0	0.0080	0	0.4111	0	0.9376	1
11	-0.2938	0	-0.4311	0	-0.0086	0	0.8796	1
12	0.0092	0	-0.0016	0	-0.0034	0	0.9987	1
13	-0.1675	0	-0.1486	0	-0.0034	0	1.0000	1
14	0.5512	0	0.6444	0	-0.0138	0	0.7802	1
15	0.5473	0	-0.4265	0	-0.0520	0	1.2533	1
16	0.6063	0	0.0294	0	-0.2816	0	1.5953	1
17	-0.0627	0	-0.5734	0	-0.1715	0	1.4129	1
18	0.2346	0	1.0796	0	0.1968	0	1.0000	1

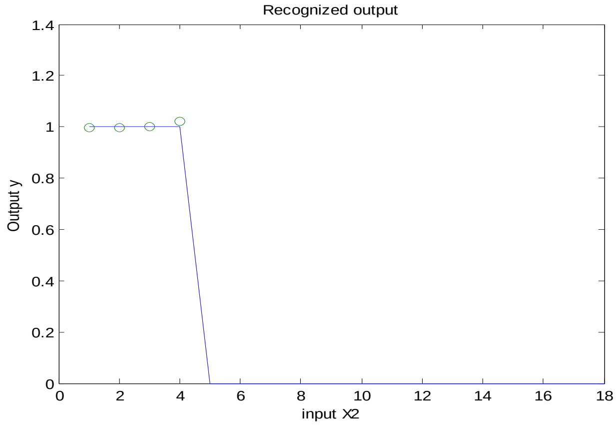

Fig 6.Recognized output for very weak muscle BP using bp

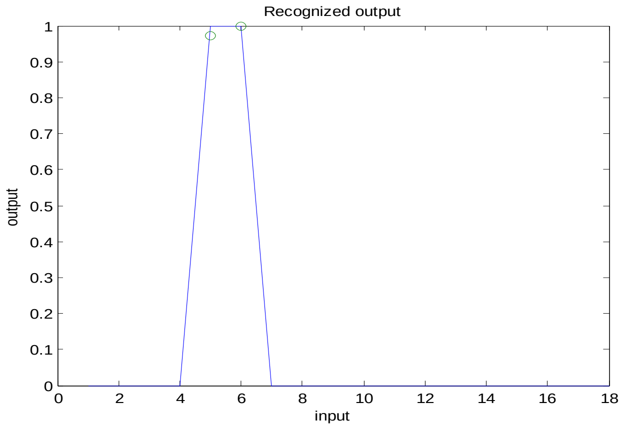

Fig 7.Recognized output for weak muscle using BP

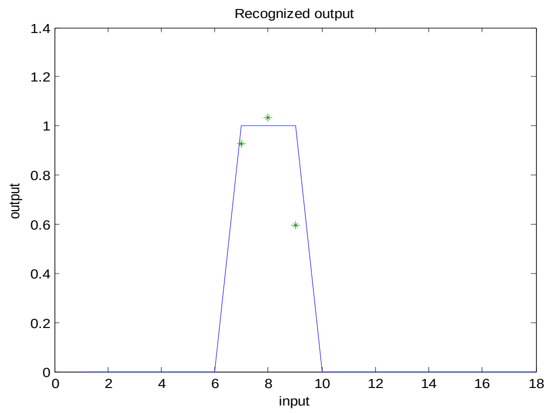

Fig 8.Recognized output for medium muscle using BP

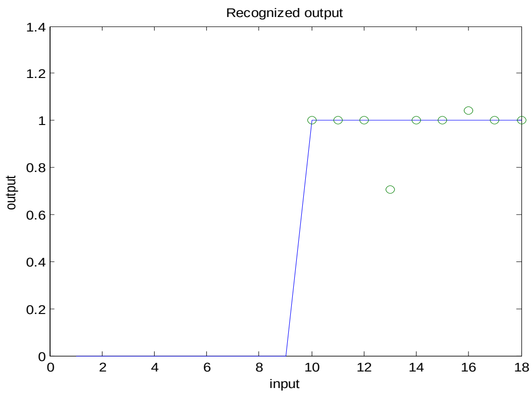

Fig 9.Recognized output for strong muscle using BP

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Table II. The Identification Results Of Surface Emg Signals For Rbf

Type of muscle / Input Signal(mv)	Very weak	Theoretical Value	weak	Theoretical Value	medium	Theoretical Value	Strong	Theoretical Value
1	0.9917	1	-0.0421	0	-0.0041	0	-0.0091	0
2	1.0210	1	0.0284	0	-0.0108	0	-0.0091	0
3	0.9649	1	-0.0158	0	-0.0412	0	-0.0091	0
4	1.0109	1	0.0094	0	0.0288	0	-0.0091	0
5	0.0167	0	0.9925	1	-0.0161	0	-0.0086	0
6	-0.0501	0	1.0094	1	0.0096	0	0.0049	0
7	0.0810	0	0.0177	0	0.9924	1	0.0710	0
8	0.0103	0	-0.0367	0	1.0094	1	-0.0478	0
9	-0.0042	0	0.0561	0	0.9841	1	0.0255	0
10	-0.0047	0	0.0025	0	0.0299	0	0.9870	1
11	-0.0047	0	-0.0083	0	-0.0551	0	1.0065	1
12	-0.0047	0	-0.0087	0	0.0810	0	0.9967	1
13	-0.0047	0	-0.0087	0	0.0112	0	1.0016	1
14	-0.0047	0	-0.0087	0	-0.0034	0	0.9992	1
15	-0.0047	0	-0.0087	0	-0.0039	0	1.0004	1
16	-0.0047	0	-0.0087	0	-0.0039	0	0.9998	1
17	-0.0047	0	-0.0087	0	-0.0039	0	1.0001	1
18	-0.0047	0	-0.0087	0	-0.0039	0	1.0000	1

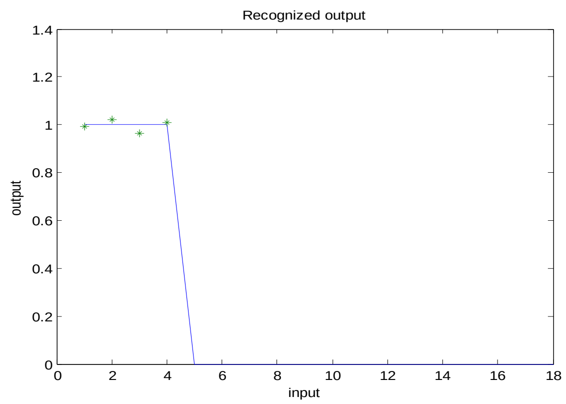

Fig 10. Recognized output for very weak muscle using RBF

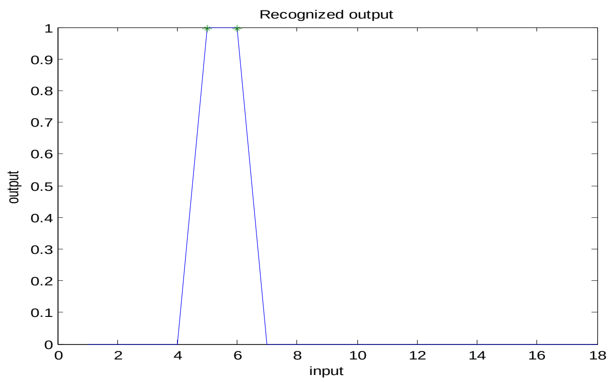

Fig 11.Recognized output for weak muscle using RBF

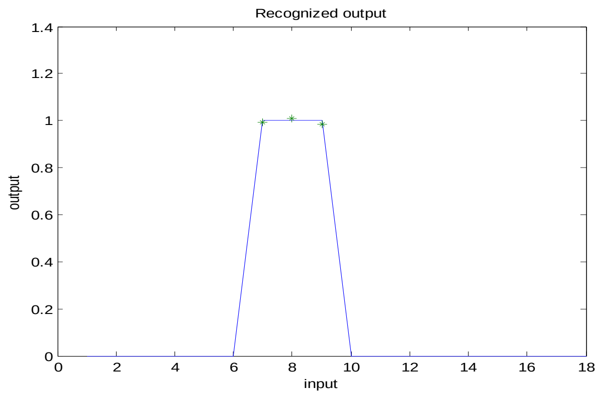

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Fig12. Recognized output for medium muscle using RBF

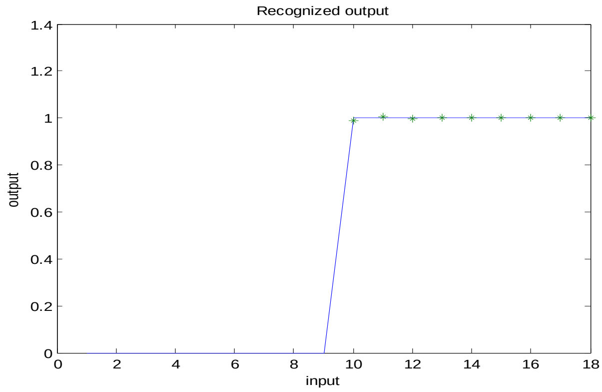

Fig13. Recognized output for strong muscle using RBF

Table 3 Recognition Rate of Two Classifiers

classifier	Very weak muscle	Weak muscle	Medium muscle	Strong muscle	Total rate
BP network	100%	94.40%	88.80%	94.40%	94.40 %
RBF network	100%	100%	100%	100%	100%

VI. CONCLUSION

The experiment shows that the peak value signal studied from SEMG can describe the feature of muscle strength pattern. Then the characteristic value is trained in RBF and BP neural network classification. After the completion of the training, the network can achieve good strength recognition rate of very weak, weak, medium and strong muscles by surface EMG by the testing data. The experiment shows that RBF neural network classification's accuracy rate is higher than BP neural network. It can effectively identify the strength of muscle pattern, and has more robustness and adaptability. So it proved to be a potential way in the field of muscle strength recognition.

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