approximation sub band of the second level of wavelet transform, e) approximation sub band of the third level of wavelet transform.

5.3. Feature Classification (Neural netork)

The MLP network with the flowing architecture and parameters was used as a classifier:

- Input layer of 64 neurons (number of wavelet coefficients).
- One hidden layer of 64 neurons.
- Output layer of 10 neurons (number of classes or numerals).
- Sigmoid activation functions for all layers.
- Weights initialized between [-1, 1] using Nguyen-Widrow initialization.
- Back propagation learning algorithm.
- Termination of training: An effective strategy of judging training adequacy is the use of a validation set. With increased training, the recognition error on the validation set will decrease monotonically to a minimum value but then it starts to increase, even if the training error continues to decrease. For better network performance, training is terminated when the validation error reaches its minimum. In our simulations, we considered about 10% of the data as the validation set.[16].

6. EXPERIMENTAL RESULTS:

6.1.Experiment 1

In this experiment we used one of the most famous wavelet transform families called Daubechies' wavelet; the Daubechies4 (db4) which has only four coefficients for low pass L (smoothing filter) and high pass filter H.

Low pass = [-0.1294, 0.2241, 0.8365, 0.4830], High pass = [-0.4830, 0.8365, -0.2241, -0.1294], After applying the wavelet filters to the training validation and test sets, we fed the MLP network by 64 coefficients of wavelet to train and test the system.

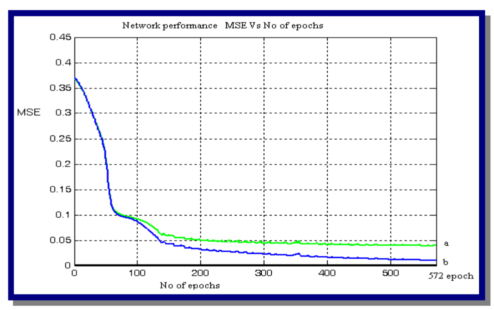

Figure 8 shows the MSE of both training and validation sets vs. No. of training epochs.

a) the MSE of the validation set, b) the MSE of the training set.

The results of the previous experiment can be seen in the confusion matrix in table (1), where the row represents the input class and the column represents the recognition result.

Table (1) the Confusion matrix of experiment 1.

	0	1	2	3	4	5	6	7
0	100	0	0	0	0	0	0	0
1	0	100	0	0	0	0	0	0
2	0	0	97.22	0	0	0	0	2.78
3	0	0	0	100	0	0	0	0
4	0	0	0	0	94.44	0	2.78	2.78
5	0	0	0	0	0	100	0	0
6	2.78	0	0	0	0	0	94.4	0
7	0	0	2.78	0	2.78	0	0	94.44

The Recognition Rate = (sum of diagonal elements) / 10= 97.22%.

6.2. Experiment 2:

In this experiment we used a biorthogonal wavelet transform filter, which has the following coefficients for low pass L (smoothing filter) and high pass filter H.

Low pass = [0, 0, 0, -0.0707, 0.3536, 0.8485, 0.3536, -0.0707, 0, 0], High pass = [0, -0.0152, 0.0758, 0.3687,-0.8586, 0.3687, 0.0758,-0.0152, 0, 0], After applying the wavelet filters to the training, validation and test sets, we fed the MLP network by 64 coefficients of wavelet to train and test the system. Figure 9 shows the MSE of both training and validation sets vs. No. of training epochs.

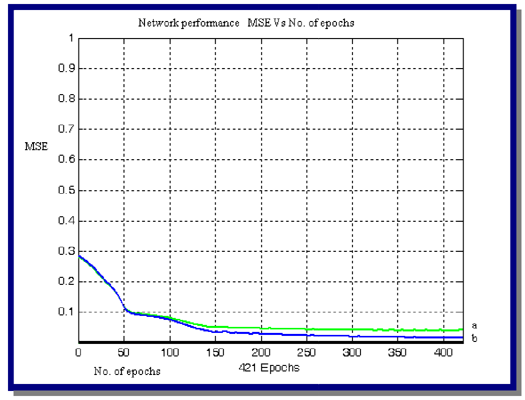

Figure 9 the MSE vs. No of training epochs,

a) MSE of the validation set b) MSE of the training set

Table (2) the Confusion matrix of experiment 2

	0	1	2	3	4	5	6	7
0	100	0	0	0	0	0	0	0
1	0	100	0	0	0	0	0	0
2	0	0	97.22	0	0	0	0	2.78
3	0	2.78	0	94.44	0	0	0	0
4	0	0	0	0	97.22	0	0	0
5	0	0	2.78	0	0	94.44	0	0
6	2.78	2.78	0	2.78	0	0	91.67	0
7	0	0	2.78	2.78	2.78	0	0	91.67

The Recognition Rate = (sum of diagonal elements) / 10= 95.56%

6.3. Experiment 3:

In this experiment we used another kind of biorthogonal wavelet transform filter, which has the following coefficients for low pass L (smoothing filter) and high pass filter H.

Low pass = [0, 0.0378, -0.0238, -0.1106, 0.3774, 0.8527, 0.3774, -0.1106, -0.0238, 0.0378],

High pass = [0, -0.0645, 0.0407, 0.4181, -0.7885, 0.4181, 0.0407, -0.0645, 0, 0], After applying the wavelet filters to the training, validation and test sets, we fed the MLP network by 64 coefficients of wavelet to train and test the system. Figure 10 shows the MSE of both training and validation sets vs. No of training epochs.

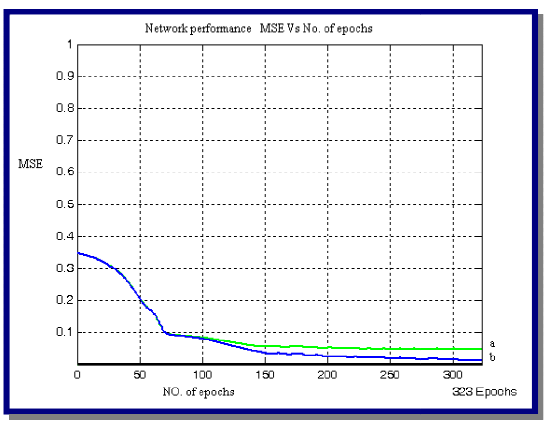

Figure 10 the MSE of both training and validation sets vs. No of training epochs, a) the MSE of the validation set b) the MSE of the training set

Table (3) the Confusion matrix of experiment 3

	0	1	2	3	4	5	6	7
0	100	0	0	0	0	0	0	0
1	0	100	0	0	0	0	0	0
2	0	0	91.67	0	2.78	0	0	2.78
3	0	0	0	97.22	0	0	0	0
4	0	0	0	0	94.4	0	2.78	0
5	0	0	2.78	0	0	94.44	2.78	0
6	2.78	0	0	0	0	0	94.44	0
7	0	0	0	5.56	2.78	0	0	91.67

The Recognition Rate = (sum of diagonal elements) / 10= 95%.

6.4. Experiment 4:

In this experiment we used another kind of biorthogonal wavelet transform filter, which has the following coefficients for low pass L (smoothing filter) and high pass filter H.

Low pass = [0 0.0331, -0.0663, -0.1768, 0.4198, 0.9944, 0.4198, -0.1768, -0.0663, 0.0331],

High pass = [0, 0, 0, 0.3536, -0.7071, 0.3536, 0, 0, 0, 0], After applying the wavelet filters to the training, validation and test sets, we fed the MLP

Figure 11 shows the MSE of both training and validation sets vs. No of training epochs.

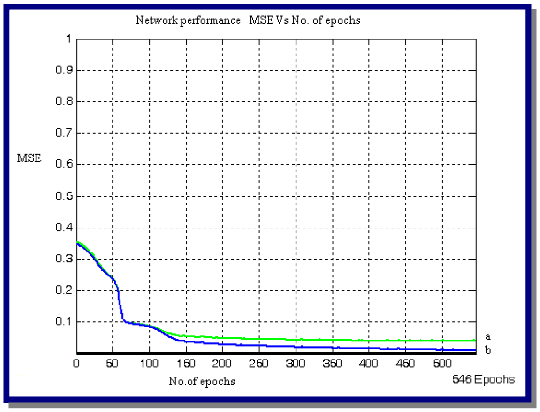

Figure 11 MSE vs. No of training epochs

a) MSE of the validation set , b) MSE of the training set

Table (4) the Confusion matrix of experiment 4.

	0	1	2	3	4	5	6	7
0	100	0	0	0	0	0	0	0
1	0	97.22	2.78	0	0	0	0	0
2	0	0	97.22	0	0	0	0	2.78
3	0	0	0	97.22	0	0	0	0
4	0	0	0	0	94.44	0	2.78	0
5	0	0	2.78	0	0	97.22	0	0
6	2.78	0	0	2.78	0	2.78	91.67	0
7	0	0	0	2.78	0	0	0	97.22

The Recognition Rate = (sum of diagonal elements) / 10= 95.28% .

7. CONCLUSION:

In a handwritten character recognition system one important work is to extract features, if we select the suitable feature, it will compress the useless information of the pattern and remain the meaningful information. Therefore, as the choice of fine features with stable ability to represent pattern features with little respect to shape variation and writing style, as reaching the crucial point to improve the performance of the handwritten numerals recognition.

In this paper we proposed feature extraction method based on two-dimensional discrete wavelet transform for off-line recognition of unconstrained handwritten numerals using back propagation neural networks as a classifier. We used the wavelet transform because it gave us space and frequency information at the same time. This means most of the energy of the signal is well represented by a few expansion coefficients. For a given image the wavelet transform produces a low frequency sub band image reflecting its basic shape and three sub band images that contain the high frequency components of the image at horizontal, vertical and diagonal directions. These components can be used to construct the feature vector in a recognition system. Two-dimensional one- level discrete wavelet transform (DWT) can be described in terms of filter banks. The calculation of the coefficients from the signal can be done efficiently. The experimental results showed that wavelet analysis is an efficient transform.

Several experiments on the wavelet filters were conducted to improve the efficiency of this system. The recognition rates of the test sets are 97.22 %, 95.56%, 95%, 95.28% respectively. We conclude the following:

- The size of the database has a major effect in the learning performance. A large database means a bigger samples with much more variations that when captured will more likely to cover different writing styles and any actual real life outcome.
- In a practical situation handwritten numerals might come translated, scaled and/or rotated. In this work normalization has been used successfully to overcome the first two problems. Rotation remains to be a problem as can be seen from the results for (6, 9) numerals. In the worth mentioning that Daubechies4 wavelet seems to have a superior performance when it comes to this point, it means that its features represented the numerals much more accurately. However, this rotation invariance issue might not make a difference for some applications where the numerals will inherently be limited in their rotation. As an example, filling applications where numerals will be confined in boxes for instance.
- Although wavelet method might be difficult to learn as a mathematical tool, but its computation is a bit easy to implement and it's not computationally intensive. In other words, wavelet as a feature-extraction tool, fits naturally with digital computer with its basis functions defined by just multiplication and addition operators. There are no derivatives or integrals.
- Note also the data visuality of transformed images will show only at a certain level of decomposition.
- The experimental results show that the proposed methods are simple and efficient representation for unconstrained handwritten numerals recognition using fewer image preprocessing.

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