Effects of the Number of Hidden Nodes Used in a Structured-based Neural Network on the Reliability of Image Classification

Weibao Zou [1,2] , Yan Li [3] and Arthur Tang [4]

[1] Department of Electronic and Information Engineering,
The Hong Kong Polytechnic University, Hong Kong

[2] Shenzhen Institute of Advanced Technology, China

[3] Department of Mathematics and Computing,
The University of Southern Queensland, Australia

[4] University of Central Florida, USA

Abstract

A structured-based neural network (NN) with Backpropagation Through Structure (BPTS) algorithm is conducted for image classification in organizing a large image database, which is a challenging problem under investigation. Many factors can affect the results of image classification. One of the most important factors is the architecture of a NN which consists of input layer, hidden layer and output layer. In this study, only the numbers of nodes in hidden layer (hidden nodes) of a NN are considered. Other factors are kept unchanged. Two groups of experiments including 2940 images in each group are used for the analysis. The assessment of the effects for the first group is carried out with features described by image intensities, and, the second group uses features described by wavelet coefficients. Experimental results demonstrate that the effects of the numbers of hidden nodes on the reliability of classification are significant and non-linear. When the number of hidden nodes is 17, the classification rate on training set is up to 95%, and arrives at 90% on the testing set. The results indicate that 17 is an appropriate choice for the number of hidden nodes for the image classification when a structured-based NN with BPTS algorithm is applied.

Keywords: hidden nodes, Backpropagation Through Structure, image classification, neural network, features set

I. INTRODUCTION

IMAGE content representation is a challenging problem in organizing a large image database. Most of the applications represent images using low level visual features, such as color, texture, shape and spatial layout in a very high dimensional feature space, either globally or locally. However, the most popular distance metrics, such as Euclidean distance, cannot guarantee that the contents are similar even though their visual features are very close in the high dimensional space. With a structured-based neural network, the image classification using features described by Independent Component Analysis (ICA) coefficients and wavelet coefficients proposed by Zou *et al* [1] [2] is an effective solution to this problem. An image is represented by a tree structure of features. Both features and the spatial relationships among them are considered since they play more important roles in characterizing image contents and convey more semantic meanings.

The supervised neural network for the classification of data structures is based on using generalized recursive neurons and the Back-Propagation Through Structure (BPTS) algorithm [3][4]-[6]. The BPTS algorithm optimizes the free learning parameters of the neural network in the node representation by using least-squares-based optimization methods in a layer-by-layer fashion, which not only make convergence speed fast, but the long-term dependency problem is also overcome [6]. The neural network of three-layers: one input layer, one hidden layer and one output layer. For a certain application, the numbers of input nodes and output nodes are fixed, normally corresponding to the input and output of the application system. The numbers of hidden nodes are influential and have dramatic impacts on the performance of a classification. It is, therefore, of interest to investigate the effects of the numbers of hidden nodes on the reliability of image classification.

The reliability of image classification is also affected by many other factors, such as input features of a neural network, methods of encoding nodes, tree structural representation of images and the amount of samples for training the neural network. In this study we only investigate effects of the number of hidden nodes. All other factors are kept unchanged.

The number of hidden nodes is determined by different methods in literature. The optimal number of hidden nodes is derived by $log(T)$, where T is the number of training samples [7]. The number of input training pattens is used to calculate the number of hidden nodes [8]. Nocera and Quelavoine proposed a method which is able to reduce the hidden nodes but still makes the neural network work properly [9]. A series of different hidden nodes were tested to classify sonar targets in [10].

The number of hidden nodes is defined as the width of a neural network [11]. The hidden layer of the neural network must be wide enough so that the result of a classification can be accurate, but too wide would result in over-fitting [12]. Therefore, the critical issue is "what is the most appropriate number of hidden nodes for a structured-based neural network for image classification?". This study aims to conduct a systematic investigation into the effects of the numbers of hidden nodes used in a structured-based neural network on the reliability of image classification.

This introduction is followed by a brief of the structured-based NN and the definition of the reliability of image classification. The feature sets and image database are then described in Sections III and IV. Two groups of experiments are carried out and the results are discussed and analysed in Section V. The analysis of the results prompts more experiments, which further support the conclusions drawn in Section VI.

II. STRUCTURED-BASED NEURAL NETWORK FOR IMAGE CLASSIFICATION

A. *Image classification with a structured-based neural network*

Connection list models have been successfully employed to solve learning tasks characterized by relatively poor representations in data structures, such as static patterns or sequences. Most structured information presented in the real world, however, can hardly be represented by simple sequences. Although many early approaches based on syntactic pattern recognition were developed to learn structured information, devising a proper syntax is often a very difficult task because domain knowledge is often incomplete or insufficient. On the contrary, graph representations vary with the sizes of input units and can organize data flexibly. Recently, neural networks for processing data structures have been proposed by Sperduti [13]. It has been shown that they can be used to process data structures using an algorithm, namely back-propagation through structure (BPTS). The algorithm extends the unfolding time carried out by back-propagation through time (BPTT) in the case of sequences. A general framework of adaptive processing of data structures is introduced by Tsoi [14] and Frasconi *et al* [3][14-15]. In the BPTS algorithm, a copy of the same neural network is used to encode every node in a graph. Such an encoding scheme is flexible enough to allow the method to deal with directed acyclic graphs of different internal structures with different number of nodes. Moreover, the model can also naturally integrate structural information into its processing. An improved BPTS algorithm by Cho *et al* is used in this study. For details, see [6] and [16].

B. Reliability in image classification

Reliability is a widely used concept in engineering and industry. A generally acceptable definition given by the British Standards Institution is as follows [17]:

"Reliability is the characteristic of an item expressed by the probability that it will perform a required function under stated conditions for a stated period of time."

In practice, the reliability of an engineering system or structure is much more complicated. In [17] there are discussions of the reliability affected by the number of hidden nodes in the case of experimental testing. In this study, we adopt the concept of reliability into the context of image classification.

In the case of image classification, it is assumed that the accuracy rate of the image classification is a good measure for the reliability. This implies that the larger the rate, the better or more reliable the performance.

III. Description of Feature Sets for Neural Network

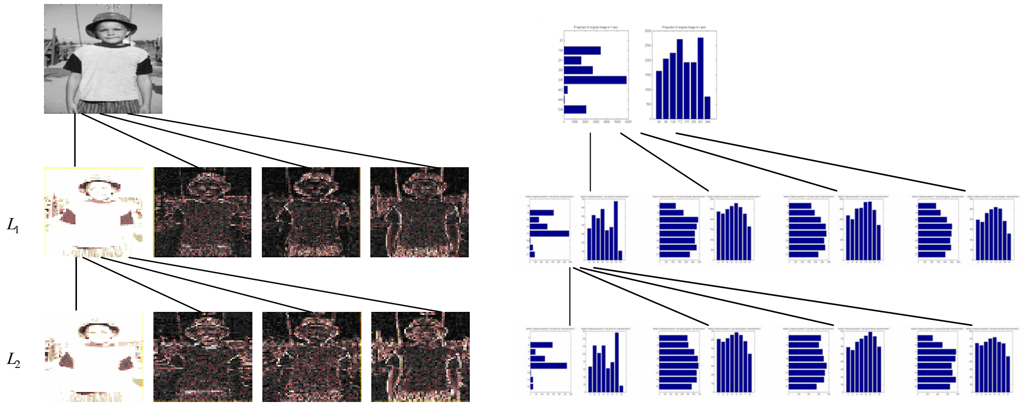
It is now pertinent to provide the description of features as attributes for the neural network and explain the methodology used in this paper.

Several factors affect the reliability of image classification. However, as explained previously, only the numbers of hidden nodes are investigated in this study. Other factors are kept unchanged.

There are two groups of experiments carried out in this section. Different features are divided into two groups: features described by wavelet coefficients used in the first group and those described by image intensities in the second group. For each group, a set of different numbers of hidden nodes are selected to analyze the relationship between the hidden nodes and the reliability of image classification. As the features are used to form the two groups, it is necessary to describe the features as below.

A. *Features extracted by wavelets transformation*

With the goal of extracting features, as an application of the wavelet decomposition performed by a computer, a discrete wavelet transformation is considered. A tree representation of an image decomposed by wavelets transformation is shown in Fig. 1(a). At level one (L_1), the original image (the top image) is decomposed into four bands. The leftmost one in the line of L_1 is the low-pass band, and the three ones on the right hand side are the high-pass bands. At level two (L_2), the previous low-pass band is decomposed into four bands. The leftmost one in the line of L_2 is the low-pass band, and the other three are the high-pass bands, which represent the characteristics of the image in the horizon, vertical, and diagonal views, respectively. From Fig. 1(a), it can be found that the basic energy and the edges of an object can be observed in low-pass band and high-pass bands at each level.



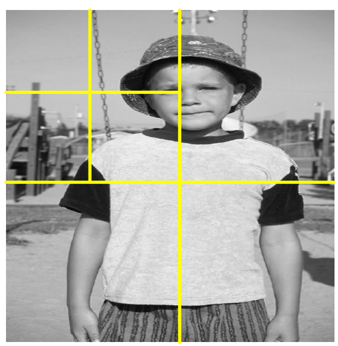
(a) (b)

Fig. 1. A tree structural representation of an image: (a) An image decomposed by wavelets transformation at two levels; (b) A tree representation of histograms of projections of wavelet coefficients corresponding to the images in (a)

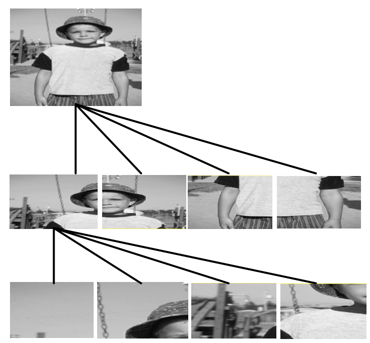
The features of an object can be described by the distribution of wavelet coefficients. It is found that wavelet coefficients corresponding to the edges of the object are greater than a certain threshold value. The wavelet coefficients which are greater than the threshold are selected into a feature set. These coefficients are projected onto the x-axis and y-axis directions, respectively. The edges of the object, therefore, can be described by the distribution of the projections of wavelet coefficients, which are statistics by histograms with 8 bins in the x direction and 8 bins in the y direction.

For example, for the high frequency bands, their features are represented by the histograms in the x-axis and y-axis directions after wavelet coefficients are projected. A similar approach is applied to the low frequency bands. Actually, such histograms can effectively represent the outline of objects. For the original image, however, its histograms are the projections of gray values of pixels, in which 8 bins are used. An intensity gray value of 127 in a pixel is set as the threshold in this paper. Features are derived by calculating the number of pixels whose intensity values are smaller than 127 in a certain part of an image. The size of the image used in Fig. 1 is 536*344 pixels (row*column). So, in y-axis, the original image is divided into 8 regions. Each region contains 67 rows. In the first region, from rows 1 to 67, there are no pixels whose gray values are smaller than 127. Therefore, the number of pixels contained in the first bar is zero. The length of the bar is also zero. In the second region, from rows 68 to 134, there are 3500 pixels whose gray values are smaller than 127. So the length of second bar is 3500. The features for the remaining regions can be deduced in a similar way. The left top figure of Fig. 1(b) is drawn as an example. The processing procedures are the same for the histograms of projections in x-axis.

The tree representation of an image described by histograms of projections of wavelet coefficients is illustrated in Fig. 1(b).



(a)



(b)

Fig. 2. A tree structural representation of an image after quartered: (a) A pyramid structural representation; (b) A tree representation of the quartered image at two levels;

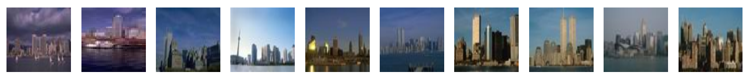
B. *Features extracted by image quartered*

Conventionally, the features for image classification are visual features, such as color, texture and shape. The intensities are used as conventional features in this study. Similar to last section, in the tree structural representation, the contents of a region are characterized by the histograms of the intensities projected onto x and y directions, respectively. The histograms are statistics with 8 bins in each direction. Totally, 16 features are taken as input attributes for the neural network.

The tree representation of the image after being quartered is shown in Fig. 2. The original image is quartered into four regions at the first level. Based on the comparisons of the entropies of these four regions, the region with the largest entropy (for example, the top left region) is quartered again into four regions at the second level. This idea is based on that if the region contains an object, the object will be very different from the background. This results in a large entropy.

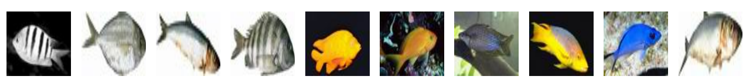
IV. Image Sets for the Experiment

Seven categories of images, namely, building, beetle, fish, grass, people, warship and vehicle, are adopted in this study. In each category of images, there are ten independent images as shown in Fig. 3.

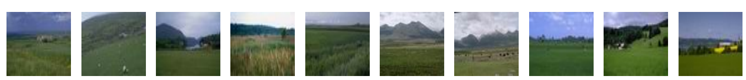


(a)

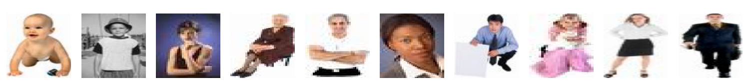
(b)



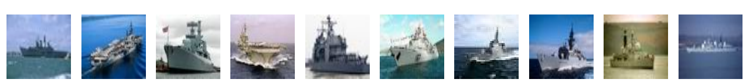
(c)



(d)



(e)



(f)

(g)

Fig. 3. Images for experiments: (a) Building; (b) Beetle; (c) Fish; (d) Grass; (e) People; (f) Warship; (g) Vehicle

There are two steps in the experiments. The first step is the neural network training and the second one is the testing. In order to make findings reliable, extra images are generated by translating the original images. For example, a window is set up in the original image, and it shifts from left to right, then top to bottom. Of course, the object must be contained in the window. However, the background is changing with the shifting window. Corresponding to each window shift, a new image is generated. Therefore, from each image, 60 new images are generated from this translational operation.

For each category of images, there are 600 derived images except the original one. Totally, 4200 images are derived from these original images. The information of the image set is tabulated in Table I. There are three kinds of data sets in the project. One is training set, another test set and the rest validation set. Together with the original images, 1470 images are used for training the neural network and other 1470 images are used for testing. The rest 1470 images are included in the validation set which is used to validate if the overfitting occurs.

TABLE I IMAGE DATABASES FOR THE STUDY

Category of images	Number of original images in each category	Number of derived images from an independent image	Number of images in each category after image translation
Building	10	60	600
Beetle	10	60	600
Fish	10	60	600
Grass	10	60	600
People	10	60	600
Warship	10	60	600
Vehicle	10	60	600
Total number	70	420	4200

V. EFFECTS OF THE NUMBERS OF HIDDEN NODES ON THE RELIABILITY OF IMAGE CLASSIFICATION

A. Selection of hidden nodes

With the two experimental groups, the number of hidden nodes varies from 10, 11, … to 43. Totally, there are fourteen different numbers of hidden nodes tested in the experiments. There are three levels of the tree structural representation of images, which contains 9 nodes. The number of epochs for training the neural network is set at 5000 in order to get reliable results. Detailed information on the hidden nodes is provided in Table II.

TABLE II INFORMATION FOR THE NUMBER OF HIDDEN NODES

Category of images		7													
Features used as attributes	Group 1	Histograms of the projections of image intensities													
	Group2	Histograms of the projections of wavelet coefficients													
Number of attributes		16													
Depth of trees		3													
Total number of nodes in tree		9													
Number of epochs		5000													
Number of hidden nodes		10	11	13	15	17	18	19	20	21	23	28	33	38	43

B. Experimental results and analysis

This section reports the classification performance. In this investigation, a single hidden-layer is sufficient for the neural classifier, which has 16 input nodes and 7 output nodes. The classification rates on training set and testing set are shown in Tables III and IV. A graphical presentation of Tables III and IV is also shown in Fig. 4(a) and (b), respectively.

TABLE III CLASSIFICATION RESULTS WITH DIFFERENT HIDDEN NODES ON TRAINING SET

Number of hidden nodes	Classification rate on training set of group 1 (%)	Classification rate on training set of group 2 (%)
10	80	82
11	78	86
13	82	87
15	80	88
17	84	90
18	81	90
19	80	89
20	82	90
21	80	90
23	79	80
28	82	91
33	84	91
38	82	90
43	84	91

TABLE IV CLASSIFICATION RESULTS WITH DIFFERENT HIDDEN NODES ON TESTING SET

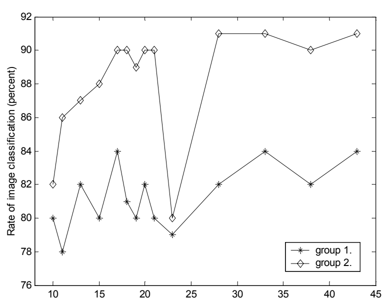
Number of hidden nodes	Classification rate on testing set of group 1 (%)	Classification rate on testing set of group 2 (%)
10	63	74
11	62	85

13	58	86
15	76	85
17	79	87
18	53	81
19	54	85
20	79	84
21	77	89
23	65	71
28	66	89
33	78	86
38	72	89
43	59	86

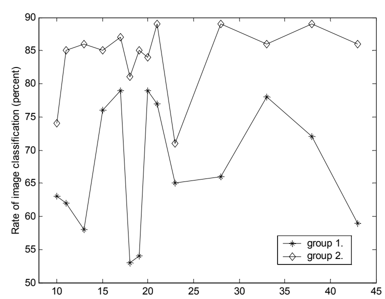
The time for training the neural network after 5000 epochs and mean-square error (MSE) are tabulated in Table V. MSE is used as a measure of the classification accuracy at root node during training the neural network. It is defined as follows:

$$MSE = \frac{\sum_{i=1}^{n}(x_i - y_i)^T (x_i - y_i)}{m \cdot n} \tag{1}$$

where, x_i is the target output at node *i*; y_i is the output at node *i*. *m* is the number of outputs of the neural network and *n* is the size of learning samples. The smaller the MSE, the better the performance. Graphical presentations of Table V are shown in Fig. 5 and Fig.6.



(a)



(b)

Fig. 4 Variations of image classification rate with different hidden nodes: (a) rate on training set; (b) rate on testing set

TABLE V CPU TIME AND MSE FOR TRAINING A NEURAL NETWORK

Number of hidden nodes	Results of group 1		Results of group 2	
	CPU time (min)	MSE	CPU time (min)	MSE
10	9.6	0.0520	27.5	0.0351
11	19.6	0.0467	29.9	0.0342
13	22.6	0.0439	31.9	0.0349

15	22.1	0.0433	41.9	0.0315
17	29.6	0.0369	33.9	0.0286
18	25.9	0.0456	36.5	0.0269
19	25.8	0.0410	38.6	0.0299
20	31.7	0.0396	45.4	0.0267
21	28.5	0.0446	40.6	0.0252
23	30.7	0.0408	42.4	0.0358
28	32.8	0.0399	45.9	0.0255
33	40.5	0.0351	57.9	0.0274
38	45.1	0.0413	60.7	0.0259
43	49.8	0.0375	69.1	0.0250

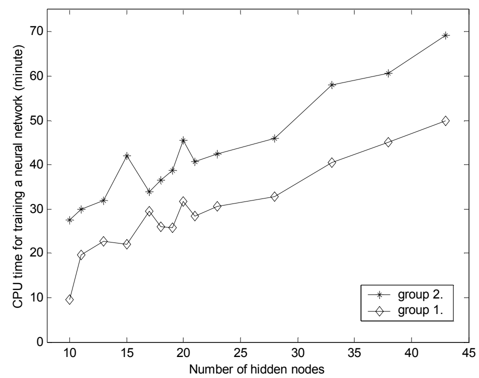


Fig. 5 Variations of CPU time with the different numbers of hidden nodes

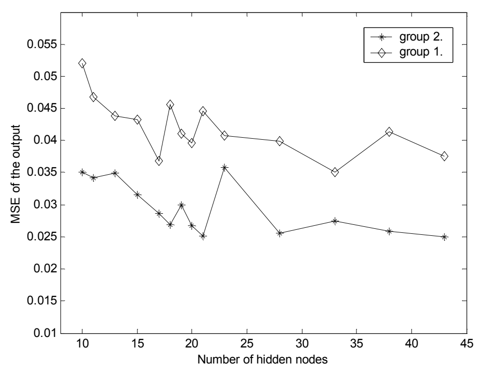


Fig. 6 Variations of MSE with the different numbers of hidden nodes

From Table III and Fig. 4(a), it is observed that the classification rate of the second group on training set is up to 91% while the rate of the first group is up to 84%. Obviously, the former is better than the latter and the rate is improved. This is because of different features used in the two groups. Clearly, the classification rates vary with the numbers of hidden nodes. When the number of hidden nodes is 17, for the second group, its classification rate on the training set is 90%, which is very close to the best one (91%).

The best rate of 91% is also achieved when the numbers of hidden nodes are 28, 33 and 43, respectively. However, these hidden numbers are much larger than 17 and cause an increase in computational complexity and much more training time. It can be derived from Table V that the CPU times, from 33.9 minutes (for 17 hidden nodes) to 45.9 minutes (for 28 hidden nodes), 57.9 minutes (for 33 hidden nodes) and 69.1 minutes (for 43 hidden nodes), are increased by 35.4%, 70.8% and 103.8%, respectively. The MSEs, from 0.0286 to 0.0255, 0.0274 and 0.0250, are decreased by 10.8%, 4.2% and 12.6%, respectively. However, the image classification rate is just improved by 1%, from 90% to 91%. Therefore, the number 17 is a trade-off value for hidden nodes for getting a better classification rate without the increase of the computation complexity.

For the first experiment group, when the number of hidden nodes is 17, the classification rate is the best (84%). The same rate is also obtained for the hidden numbers of 33 and 43. However, the least CPU time is required when the hidden nodes are 17. This indicates that when the number of hidden nodes is 17, the classification rate is better or the best with a fast speed.

With the trained neural network, the testing is carried out with another set of images not used in the training set. From Table IV and Fig. 4(b), it is found that the classification rate for group 2 is up to 89%. With 17 hidden nodes, its classification rate is 87%, close to the best. For the result of group 1, the rate is up to 79%. For 17 hidden nodes, its classification rate is the best. Apparently, the effects of the number of hidden nodes on the reliability of image classification are non-linear. The experiment results are more reliable when the number of hidden nodes is 17.

C. *Analysis of overfitting*

It is well known that overfitting can easily occur for this type of neural networks, and the errors due to overfitting are related to the number of hidden nodes for the same problem. Therefore, the training epoch for the neural network is a crucial aspect of this case study and it is analyzed in this section.

The overfitting is investigated by using the third data set, the validation data set. In the experiments, different numbers of epochs are tested from 1 to 5000 with a gap of 1. The classification rate validated by the validation data set with epochs at 500, 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500 and 5000 are presented in Table VI. The hidden nodes for the experiments are 10, 17 and 38, respectively. Its graphic representation of Table VI is also given in Fig. 7.

From Table VI and Fig.7, it is noticed that, for hidden nodes of 10, when training epoch is 500, its validated classification rate is 55% for group 1. With the increase of epochs, its classification rate increases. From epochs of 3000 to 4000, the rates remain the same at 62%. After that, the rate increases to 63%. From epochs of 4500 to 5000, the rates sit at 63% and do not change. Overall, the rate is becoming larger when the numbers of epoch is increasing. It eventually keeps almost the same value. It is validated that the overfitting dose not occur during training the neural network. For hidden nodes of 17 and 38, the same experimental results are obtained. They are similar for the results obtained by the hidden nodes of 11, 13, 15, 18, 19, 20, 21, 23, 33, 38 and 43. For the group 2, the similar results are obtained and it is concluded that the overfitting dose not occur in this study.

TABLE VI CLASSIFICATION RATE ON VALIDATION SET FOR GROUP 1

Number of hidden nodes	Number of epochs	Classification rate on training set (%)	Classification rate on validation set (%)
10	500	72	55
	1000	77	58
	1500	78	60
	2000	79	61
	2500	79	61
	3000	79	62
	3500	79	62
	4000	79	62
	4500	80	63
	5000	80	63
17	500	72	61
	1000	76	66
	1500	79	70
	2000	80	71
	2500	81	74
	3000	81	74
	3500	82	75
	4000	83	77
	4500	84	79
	5000	84	79
	500	73	55

	1000	77	58
	1500	79	60
	2000	81	62
	2500	81	62
28	3000	82	65
	3500	82	65
	4000	82	65
	4500	82	65
	5000	82	65

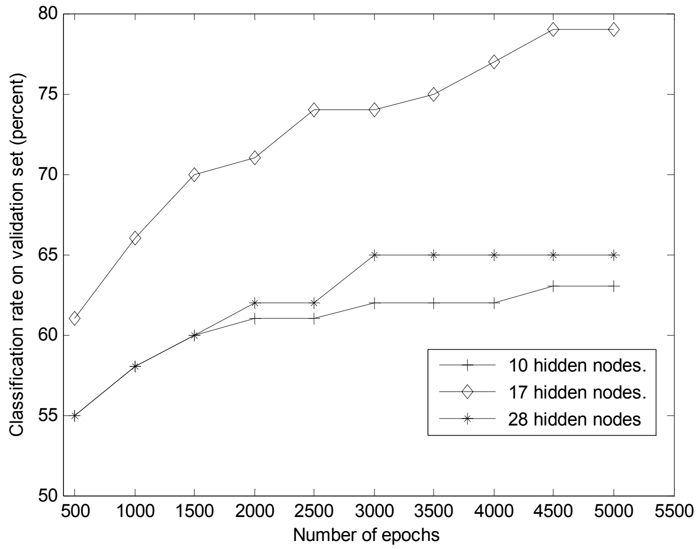


Fig. 7 Variations of classification rate on validation set with epochs of group 1

D. Statistical analysis of results

As observed from Tables III and IV, and Fig. 4, the classification rates vary with the number of hidden nodes. It is of great interest for researchers to examine whether or not the variations are of significance. Otherwise, any number of hidden nodes can be selected. In practice, however, it is unlikely as observable from Fig. 4. To test the significance, a t-test is carried out for the classification rates on both training and testing sets.

The test statistics take the following form [18]:

$$t = \frac{\bar{x} - \mu}{s / \sqrt{n}} \tag{2}$$

where, n is the number of samples;

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{4}$$

and μ is the smallest value among the samples.

Student's t-test is separately carried out for the two groups. In this analysis, only the first group on the training set is taken as an example. In the group, the numbers of hidden nodes are 10, 11, 13, 17, 18, 19, 20, 21, 23, 28, 33, 38 and 43, respectively. The smallest rate on training set is 78% when the hidden nodes are 11. Therefore, one can make a hypothesis

$$H_0\text{:}\ \ \mu\text{=}0.78$$

and the corresponding null hypothesis H_0 is

$$H_a\text{: not } H_0$$

Here, n=14 and resultant $t = 6.47$. These values are needed to be checked against the threshold in a standard table of t values. In this example there are 13 degrees of freedom (df) (= n-1); at 95% confidence level ($\alpha = 0.05$), $t_{\alpha/2}(13)$ is 2.16 in the table of t values. As the t value obtained from this example is 6.47 which is greater than 2.16, H_0 is rejected in favour of H_a and it is concluded that the variation of rate values is significant at 95% confidence level.

TABLE VII. SIGNIFICANCE TEST ON CLASSIFICATION RATE*

Classification rate	t-Test results for rate values	
	Group 1	Group 2
Rate on training set	Y (6.47)	Y (8.98)
Rate on testing set	Y (5.61)	Y (9.08)

* Y = significant variation.

$t_{\alpha/2}(13) = 2.16$.

TABLE VIII. SIGNIFICANCE TEST ON MSES AND CPU TIME*

MSEs and CPU time	t-Test results for MSEs
MSE for group 1	Y (5.85)

MSE for group 2	Y (4.12)
CPU time for group 1	Y (7.16)
CPU time for group 2	Y (4.78)

* Y = significant variation.

$t_{\alpha/2}(13) = 2.16$.

Similar tests have also been carried out for the second group. The results are shown in Table VII. T-test has also been carried out for rate values on testing set and the results are included in Table VII. Meanwhile, the MSEs and CPU times on the training set are tested by t-test too. The results are provided in Table VIII. In these tables, '*Y*' means a significant variation. It is noticed that, with different hidden nodes, the variations of classification rates, MSEs and CPU times are very significant for all the experimental results.

From the t-test results, it is observed that the effects of the number of hidden nodes on the image classification rate are significant. Therefore, the number of hidden nodes must be selected carefully.

VI. Discussion

The experimental results in this paper demonstrate that the effects of the number of hidden nodes on the reliability of image classification are significant. Moreover, the rate of image classification is consistently better when the number of hidden nodes is 17. This means that the performance of image classification is reliable. However, there are a few issues to be cleared up before a reliable conclusion can be drawn.

From Table III and Fig. 4(a), it can be seen that when the number of hidden nodes of 21 is used, the rate of classification is 90% for the group 2; the same as the one when the hidden nodes are 17. However, its MSE values are smaller than the ones with the hidden nodes of 17 (by 11.9%). In addition, for the curve of group 2 in Fig. 4(b), it is noticed that when the number of hidden nodes is 21, the classification rate on the testing set is the highest. Therefore, the questions arising are:

(a) Can one be sure that, when the number of 21 is used for hidden nodes, the results are consistently good?

(b) If yes, which should be recommended, ‘‘the number of 17’’ or ‘‘the number of 21’’?

In order to obtain more reliable conclusions for this study, a group of experiments with different kind of features used as attributes are conducted for further investigation. In the experiments, the features sets are mixed, which consist of two parts: wavelet coefficients and ICA coefficients.

A. Description of mixed features sets

As described in Section III, the features are described by wavelet coefficients in low-pass bands and high-pass bands. The distribution of their histograms of projections of wavelet coefficients in low frequency bands is very different for different images. But, in high frequency bands, their histograms are similar. Big differences in histograms can benefit the image classification. Therefore, ICA is conducted to extract features from these three high frequency bands in order to improve the image classification. For the details of features extracted by ICA, see [1].

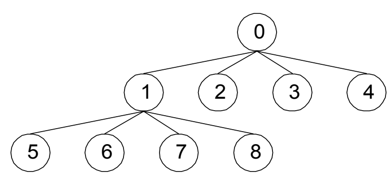


Fig. 8. An illustration of feature sets adopted in nodes: wavelet features used in nodes 0, 1 and 5; ICA features used in nodes 2, 3, 4, 6, 7, 8.

The wavelet features are statistics by histograms of projections of wavelet coefficients with 8 bins in the directions of x and y, respectively. Totally, there are 16 parameters in wavelet features set at each node. For ICA features set, there are also 16 parameters. These 16 parameters in both ICA and wavelet features sets are combined together as input attributes for the neural network. In the tree structural representation of an image, wavelet features are used in nodes 0, 1, and 5. ICA features are used in nodes 2, 3, 4, 6, 7, 8. It is illustrated in Fig. 8. The input attributes for the neural network are described in form of a mixed matrix as shown in equation (5).

$$U = \begin{bmatrix} h_{0,1} & h_{0,2} & \cdots & h_{0,16} \\ h_{1,1} & h_{1,2} & \cdots & h_{1,16} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,16} \\ & & \cdots & \\ w_{4,1} & w_{4,2} & \cdots & w_{4,16} \\ h_{5,1} & h_{5,2} & \cdots & h_{5,16} \\ w_{6,1} & w_{6,2} & \cdots & w_{6,16} \\ & & \cdots & \\ w_{8,1} & w_{8,2} & \cdots & w_{8,16} \end{bmatrix} \quad (5)$$

where, $h_{i,j}$ refers to the *j*-th histogram value of the *i*-th node ($i = 0, 1, 5$) and is a parameter of wavelet features expressed by histograms of projections of wavelet coefficients; $w_{k,j}$ is the parameter in *W* of the *k*-th node; $k = 2,3,4,6,7,8$ and $j = 1, \cdots, 16$. It is a parameter of ICA features expressed by the inverse matrix of *W*.

TABLE IVV. EXPERIMENTAL RESULTS OF GROUP 3

Number of hidden nodes	Classification rate on training set (%)	Classification rate on testing set (%)	CUP time (min)	MSE
10	86	83	25.8	0.0322
11	87	85	29.4	0.0302
13	88	86	31.4	0.0251
15	89	86	33.0	0.0245
17	92	89	33.3	0.0182
18	91	87	34.4	0.0189
19	91	86	34.5	0.0219
20	92	87	35.7	0.0194
21	92	89	41.9	0.0175
23	91	88	40.9	0.0185
28	89	86	42.4	0.0194
33	91	87	55.1	0.0153
38	95	90	48.1	0.0127
43	94	90	65.3	0.0120

TABLE VV. Significance test on classification results of group 3*

Classification results	t-Test results
Rate on training set	Y (6.75)
Rate on testing set	Y (7.69)
CPU time	Y (4.72)
MSEs	Y (5.33)

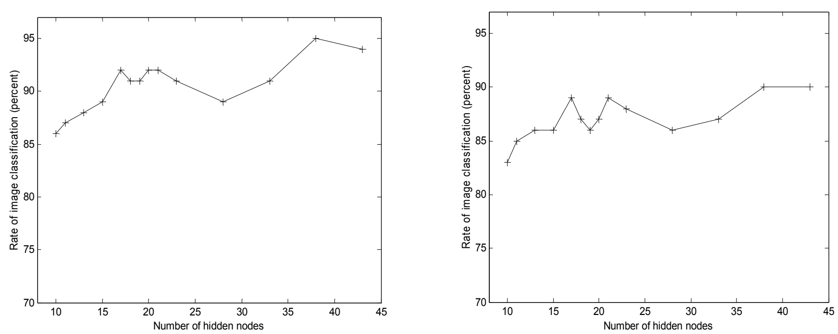
* *Y* = significant variation.

$t_{\alpha/2}(13) = 2.16$.

B. Experimental results

The same numbers of hidden nodes as in the previous two groups of experiments are tested. The results are shown in Table IVV. The significance tests of classification rates, MSEs and CPU times are also carried out, and the results are tabulated in the Table VV. The relationship between the reliability of the classification and the numbers of hidden nodes on training and testing sets are also graphically presented in Fig. 9, the CPU times in Fig. 10 and the MSE values in Fig. 11. The classification rates validated by the validation set with different number of epochs are presented in Table VVI. Its graphic representation is also given in Fig. 12.

The experiment results presented above vary significantly. When the hidden number is 17, the results are better which is in consistent with the findings obtained in Section V.



(a) (b)

Fig. 9 Variations of image classification rate with different numbers of hidden nodes: (a) rate on training set; (b) rate on testing set

TABLE VVI CLASSIFICATION RATE ON VALIDATION SET FOR GROUP 3

Number of hidden nodes	Number of epochs	Classification rate on training set (%)	Classification rate on validation set (%)
10	500	77	71
	1000	80	76
	1500	81	77
	2000	82	79
	2500	84	80
	3000	84	80
	3500	85	81
	4000	85	81
	4500	85	81
	5000	86	83
17	500	76	72
	1000	83	79
	1500	86	81
	2000	87	82
	2500	89	84
	3000	90	85
	3500	90	85

	4000	91	87
	4500	91	87
	5000	92	89
28	500	78	72
	1000	79	74
	1500	81	77
	2000	84	79
	2500	85	81
	3000	85	81
	3500	87	83
	4000	88	85
	4500	89	86
	5000	89	86

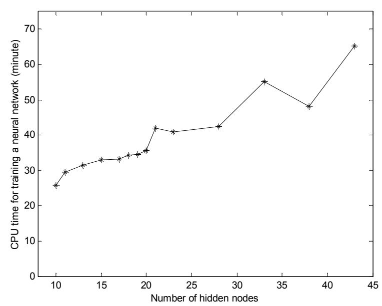


Fig. 10 Variations of CPU time with the different numbers of hidden nodes for group 3

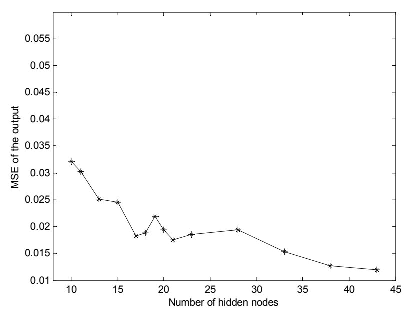


Fig. 11 Variations of MSEs with the different numbers of hidden nodes for group 3

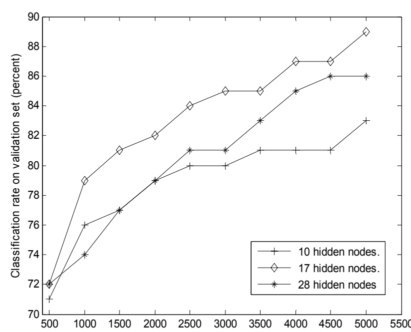


Fig. 12 Variations of classification rate on validation set with epochs of group 3

VII. Conclusion

The effects of the number of hidden nodes on the reliability of image classification with a structured-based neural network are investigated in this paper. The number of hidden nodes is the only factor considered in this study. The other factors remain unchanged. Two groups of experiments have been conducted for the research. In order to make the findings more reliable, an extra group of experiments with a different features set are carried out for the further investigation. Similar results are also obtained. From the results, it is found that the effects of the number of hidden nodes on the reliability of image classification are significant and non-linear. It is also observed that, for a structured-based NN, when the number of hidden nodes is 17, it always yields a reliable result.

All the conclusions in this paper are based on the experiment results on our image database using a structured-based neural network. It, therefore, cannot be generalized to other image classification techniques. The number of 17 can be used as a guideline to select the hidden nodes for a structured-based NN with BPTS algorithm, which is a trade-off value between the classification rate and the computational complexity.

Acknowledgment

The work described in this paper was partially supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project no. PolyU 5229/03E).

The authors greatly appreciate the valuable comments and suggestions received from the reviewers of this paper.

References

[1] W. Zou, Y. Li, K. C. Lo and Z. Chi, 2006, "Improvement of Image Classification with Wavelet and Independent Component Analysis (ICA) Based on a Structured Neural Network", *Proceedings of IEEE World Congress on Computational Intelligence'2006 (WCCI'2006),* Vancouver, Canada, July 16-21, 2006, 7680-7685.

[2] W. Zou, K. C. Lo and Z. Chi, "*Structured-based Neural Network Classification of Images Using Wavelet Coefficients*," Proceedings of Third International Symposium on Neural Networks (ISNN), Lecture Notes in Computer Science 3972: Advances in Neural Networks-ISNN2006, Chengdu, China, May 28-June 2, 2006, part II: 331-336, Springer-Verlag.

[3] C. L. Giles, M. Gori, "*Adaptive Processing of Sequences and Data Structures*," Springer, Berlin New York, 1998.

[4] A. Sperduti, A. Starita, "Supervised Neural Networks for Classification of Structures," *IEEE Trans. on Neural Networks*, vol 8, Mar 1997, pp. 714-735.

[5] C. Goller, A. Kuchler, "Learning Task-dependent distributed representations by Back-propagation Through Structure," *Proc. IEEE Int. Conf. Nerual Networks*, pp. 347-352, 1996.

[6] S. Y. Cho, Z. R. Chi, W. C. Siu and A. C. Tsio, "An improved algorithm for learning long-term dependency problems in adaptive processing of data structures," *IEEE Trans. On Neural Network,* vol. 14, pp 781-793, July, 2003.

[7] N. Wanas, G. Auda, M. S. Kamel, and F. Karray, "On the optimal number of hidden nodes in a neural network", *IEEE Canadian Conference on Electrical and Computer Engineering*, vol. 2, pp 918 – 921, 1998.

[8] G. Mirchandani and W. Cao, "On Hidden Nodes for Neural Nets", *IEEE Trans. On Circuits and Systems*, vol. 36 (5), pp 661-664, 1989.

[9] P. Nocera, R. Quelavoine, "Diminishing the number of nodes in multi-layered neural networks", *IEEE World Congress on Computational Intelligence*, pp4421-4424, 1994.

[10] R. P. Gorman and T. J. Sejnowski, "Analysis of Hidden Units in a Layered Network Trained to Classify Sonar Targets", *Neural Networks*, vol. 1, pp 75-89, 1988.

[11] R. Rojas, "Networks of Width One Are Universal Classifiers", *Proceedings of the International Joint Conference on Neural Networks*, pp3124-3127, 2003.

[12] "How Many Hidden Units Should I use?" http://www.faqs.org/faqs/ai-faq/neural-nets/part3/section-10.html (access, Aug. 29, 2007)

[13] A. C. Tsoi, "*Adaptive Processing of Data Structures: An Expository Overview and Comments*," Technical report, Faculty of Informatics, University of Wollongong, Australia, 1998.

[14] A. C. Tsoi, M. Hangenbucnher, "Adaptive Processing of Data Structures. Keynote Speech," *Proceedings of Third International Conference on Computational Intelligence and Multimedia Applications* (ICCIMA '99), 2-2 (summary), 1999.

[15] P. Frasconi, M. Gori, A. Sperduti, "A General Framework for Adaptive Processing of Data Structures," *IEEE Trans. on Neural Networks*, vol 9, pp. 768-785, 1998.

[16] S. Cho, Z. Chi, Z. Wang, W. Siu, "An Efficient Learning Algorithm for Adaptive Processing of Data Structure," *Neural Processing Letters*, vol. 17, 175-190, 2003.

[17] G. Dummer and R. Winton, "***An Elementary Guide to Reliability,***" 3rd edition, Pergamon Press, 47p, 1986.

[18] G. W. Snedecor and W. G. Cochran, "*Statistical Methods*", Iowa State University press, 507 p, 1989.