An Efficient and Accurate Artificial Neural Network through Induced Learning Retardation and Pruning Training Methods Sequence

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Abstract: The induced learning retardation method involves the temporary inhibition of the artificial neural network's active units from participating in the error reduction process during training. This stimulates the less active units to contribute significantly to reduce the network error. However, some less active units are not sensitive to stimulation making them almost useless. The network can then be pruned by removing the less active units to make it smaller and more efficient. This study focuses on making the network more efficient and accurate by developing the induced learning retardation and pruning sequence training method. The developed procedure results to faster learning and more accurate artificial neural network for satellite image classification.
Keywords: Artificial Neural Networks, Pruning, Training.

1. Introduction

Artificial neural network (ANN) has recently been included in the list of analytical tools for satellite image classification. Unlike the conventional statistical classifiers, ANN is distribution assumption independent and therefore more robust when distributions are strongly non-Gaussian [3,5]. One of the most important constraints of using ANN is its efficiency. Training ANN for satellite image classification is computationally expensive. Furthermore, it has been observed that the longer an ANN is trained, the more specific it will become, reducing its capability to generalize resulting to its low classification accuracy [1,4].

Recent experiments demonstrated that increasing the learning speed of an artificial neural network could be achieved by temporarily retarding its learning capability during training [2]. The process involves the temporary inhibition of the network's active units from participating in the error reduction process. Through this, the less active units are stimulated to contribute significantly to reduce the ANN error during training, increasing the network's learning speed. However, some of the identified less active units are not sensitive to stimulation making them almost useless in reducing the network error. Hence, increasing further the learning speed of the ANN during training is possible by removing the inactive units. The process makes the ANN smaller requiring lesser number of repetitive computations, making it to be more efficient during training and actual classification. The process is called artificial neural network pruning.

This study focuses on increasing the learning speed and accuracy of the artificial neural network by developing the induced learning retardation and pruning sequence training method. The procedure is tested to classify a Landsat TM data of the study site in Tochigi Prefecture, Japan. The developed procedure results to faster, accurate and more efficient ANN for satellite image classification.

2. Methods

1) Artificial Neural Network Structure

A multi-layer perceptron trained by the back-propagation algorithm [6] using the gradient descent training method was used in this experiment. The ANN has one hidden layer with 30 nodes. In this experiment, the input layer has 5 nodes for the 5 Landsat TM bands (bands 1 to 5) and the output layer consisted of 7 nodes reflecting the 7 land cover classes. The structure of the ANN is shown in fig. 1. In this study, ANN training was stopped after the trained network reached an accuracy of at least 90% using the training data. A software written using Microsoft Visual C++ was used to implement the experiments.

2) The Training Method

The training method involved the implementation of the induced learning retardation and pruning techniques in sequence during training. The identification of the active and less active units of the ANN is central to this experiment. Active ANN units are those connections that have higher level of participation in the error reduction process during training. The level of participation of the ANN units was determined through the magnitude of the changes of their values during training. The higher is the change, the more active is the unit. The procedure of the identification of the active and less active ANN units during training is described in detail by the work of Bandibas and Kohyama [2].

The summary of the different steps involved during the ANN training using the developed procedure is shown in fig. 2. The proposed procedure is straightforward. As shown in the figure, the learning retardation method was first implemented at the start of training. This method is described in detail by the work of Bandibas and Kohyama [2]. After implementing the procedure, the ANN connections that had insignificant contribution to the error reduction process were identified. This was followed the pruning procedure where the identified less active ANN units were removed. For comparison purposes, an ANN was also trained conventionally.

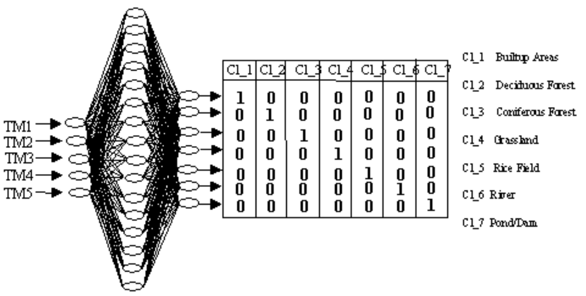

Fig 1. The ANN structure and the output training patterns representing the 7 land cover classes.

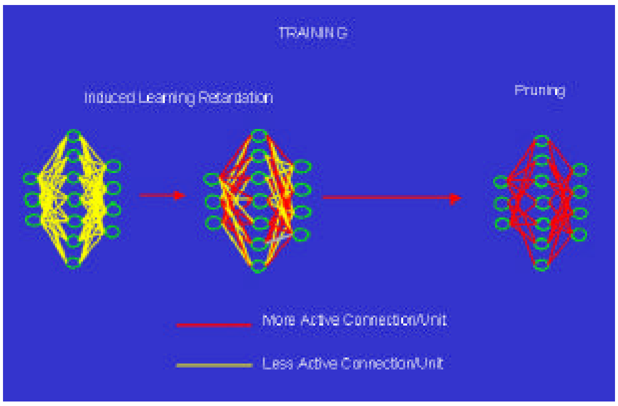

Fig. 2. The learning retardation and pruning sequence method.

3) ANN Training

In this study, five training runs were implemented for the developed procedure. The same number of training runs was implemented for the ANN trained using the conventional method. For an easy and consistent comparison of the generalization capability of the trained ANN, the accuracy obtained using the training data was used as the convergence criterion. In this study, all training runs were stopped when the network's accuracy was at least 90% using the training data. Hence, the ANN accuracy was determined at the end of every training iteration.

3. Results and Discussion

The results of the experiment clearly show that the developed ANN training technique results to an efficient and accurate neural network. Fig. 3 shows the changes of the root mean square error (RMS) at the early stage of the ANN training. Using the induced learning retardation-pruning method clearly resulted to the rapid reduction of the network error compared to the conventional method. The rapid decline of the ANN error at the early stage of training also resulted to shorter training time. Fig. 4 shows that the developed training procedure resulted to training iterations 3 times lower than the conventional training method.

It has been observed that ANN accuracy is always related to its ability to generalize. One of the factors that affect the ANN's generalization capability is training time. The longer an ANN is trained, the better it classifies the training data, but the more likely it is to fail in the classification of new data because it may become over-specific [4]. This observation is consistent with the result of the study. In this experiment, the use of the developed training technique significantly reduced the training time of the ANN. Consequently, the generalization capability of the ANN is significantly higher compared to the one trained longer. Fig. 5 clearly shows that using the developed techniques resulted to trained ANN that is more accurate compared to the one trained conventionally. Fig. 6 shows the classified image using the developed procedure and the conventional ANN training method.

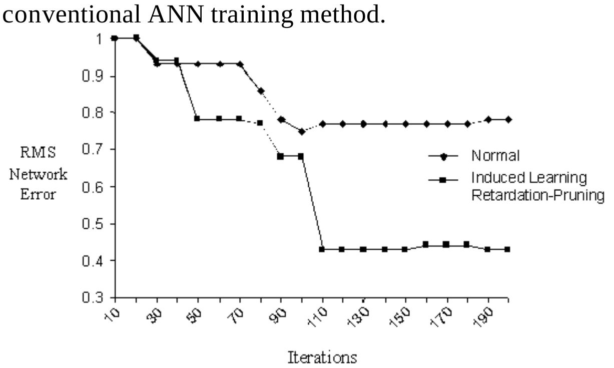

Fig. 3. The ANN Root Mean Square error at the early stage of training using the conventional and the induced learning retardation-pruning training methods.

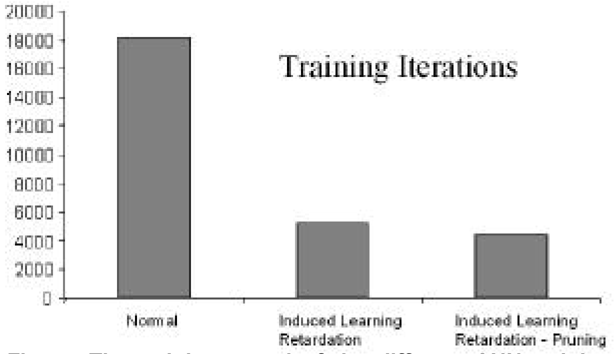

Fig. 4. The training speed of the different ANN training methods.

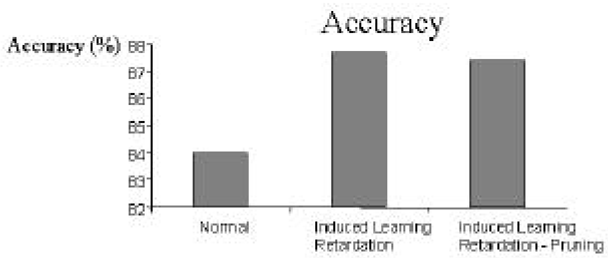

Fig. 5. The accuracy of the trained ANN using different training methods.

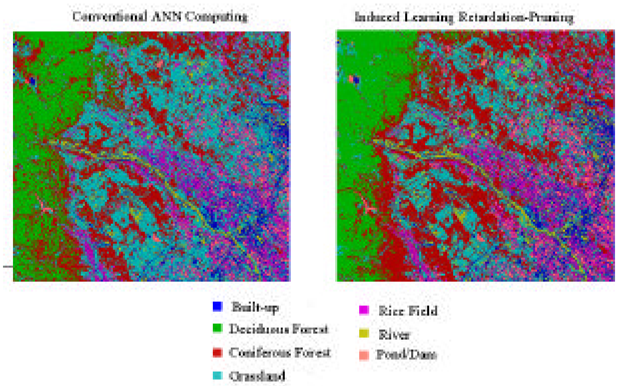

Fig. 6. The classified satellite image using the ANN trained conventionally and the one trained using the induced learning retardation- pruning sequence.

4. Conclusion

The use of the induced learning retardation-pruning sequence during ANN training increases the learning speed of the network. The developed procedure also produces trained ANN that is more efficient and accurate for satellite image classification.

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