A MODULAR NEURAL NETWORK APPROACH TO CHEMICAL CONTENT ANALYSIS OF VEGETATION

[1]N. Kussul, [1]V. Yatsenko, [2]A. Sachenko, [3]G. Markowsky,
[1]A. Sydorenko, [1]S. Skakun, [2]S. Ganzha

[1]Space Research Institute NASU-NSAU, 40 Glushkov Ave 03187 Kiev,
Ukraine, inform@space.is.kiev.ua

[2]Institute of Computer Information Technologies
Ternopil Academy of National Economy
3 Peremoga Square, 46004, Ternopil, Ukraine, itu@tanet.edu.te.ua

[3]Department of Computer Science, 5752 Neville Hall, University of Maine,
Orono, ME 04469-5752, markov@cs.umaine.edu

Abstract

The state of a plant affects its chlorophyll content, which in turn, affects the way the plant reflects light. Consequently, the characteristics of the reflected light can be used to determine the health of a plant. This raises the possibility of monitoring large areas of vegetation by analyzing the reflectance of the plants in the area. This paper discusses the use of neural networks for analyzing the reflectance of plants. We discuss two approaches: the classical approach and a modular approach and demonstrate that the modular approach has certain advantages for analyzing the reflectance of plants.

1. Introduction

The spectral characteristics of light that is reflected from earth objects can provide important and convenient information for remote investigations. They can be used to determine the infection and pollution levels of vegetation, e.g., as might occur in a biological terrorist attack. In [1] it is shown that plant states can be deduced by measuring the amount of light reflected at different wavelengths. In particular, the chlorophyll content of plants can be determined in this manner.

Figure 1 shows the spectral curves of winter wheat as determined by the Institute of Physiology and Genetics (Ukraine) [2]. The problem of chemical composition detection, in this case chlorophyll concentration, is a pattern recognition problem that can be handled by neural networks (NN).

Each spectral curve in Figure 1 contains 350 points. This determines the dimension of the NN input layer. The high dimension of the input data and the large training set suggests the use of a modular NN architecture. We can reduce the input space dimension either by informative feature extraction or by problem decomposition. Informative feature extraction from input data will be investigated in the future. Informative feature extraction can be done by principal component analysis, or by other techniques such as non-linear, self-organizing methods. In this work we reduce problem complexity by decomposing the problem into subproblems, each of which can be solved by a neural network. This approach is called the modular NN approach [3].

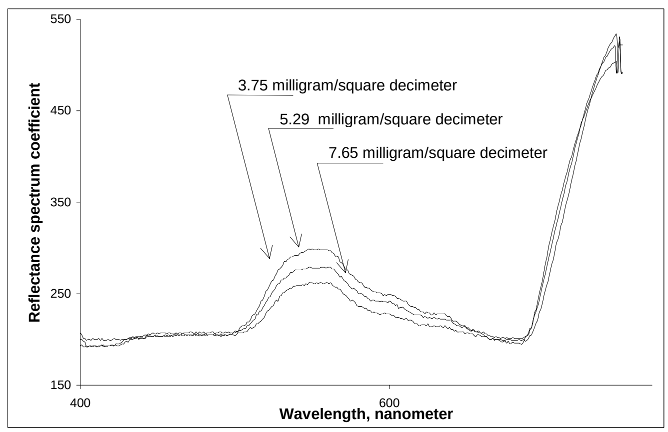

Figure 1. Some Spectral Curves Showing How Reflectance Varies With Wave-Length For A Constant Chlorophyll Content.

In the first stage of our modular NN the input data are divided into 2 classes — damaged and undamaged. In subsequent stages only the data classified as damaged are analyzed. This approach decreases the dimension of the training set in the problem of chemical composition determination and reduces the training time of the NN. We illustrate the practical capabilities of this technique by analyzing the state of the winter wheat crop.

2. A Modular Neural Net Solution

Figure 2 shows the modular NN used to determine the level of plant damage (infection). The classifier executes data pre-processing (brute classification), dividing input data into 2 classes: damaged and undamaged. There are many choices for the classifier design: potential functions, RBF-classifier, RTC-classifier, etc. Since there were only a small number of examples in the training set, a single-layered perceptron with supervised learning was chosen for the classifier. If the classifier output is 0, i.e. the input pattern is classified as damaged, the data is sent on to the interpolator. The interpolator output gives the exact chlorophyll content of the plant. The interpolator was implemented as a multi-layered, feed-forward NN. Back propagation and second order optimization methods were used for training the interpolator.

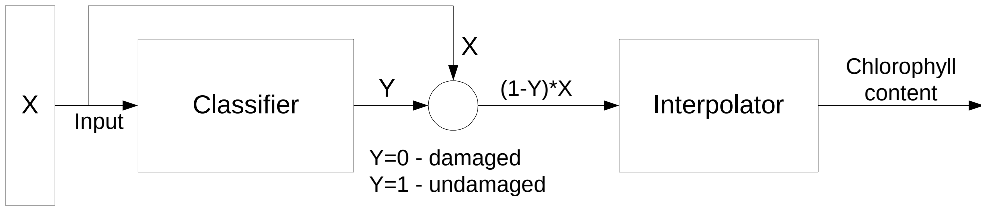

Figure 2. A Modular Neural Network For Solving The Chlorophyll Content Problem

3. A Traditional Neural Net Solution

Determining the chlorophyll content can also be done with a traditional neural network. To get a fair comparison between the traditional and modular approach we determined the best training parameters and the quantitative rates of training for the traditional network.

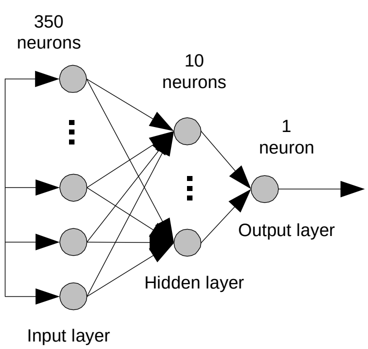

Figure 3. The Architecture Of A Traditional NN.

The traditional network we designed was a feed-forward neural network. It has one hidden layer with 10 neurons, an input layer with 350 neurons, and an output layer with one neuron. The activation functions for the first and second layers are sigmoid, while for the output layer it is linear. All layers have learning coefficients of 0.1 and moment coefficients of 1.15. The initial values of the weight matrices were randomly chosen from [-1, 1]. The neural network was trained in interpolator mode with precision 0.05 using chlorophyll output values, a subset of which are displayed in Figure 1. The training results are shown in Table 1. The experiments were run for different initial values of weight coefficients and for different training methods of the first and the second orders.

Table 1. Number of Training Epochs for the Traditional NN using Three Different Initial Estimates

Training Methods	Number of training epochs		
Fletcher-Powell method	did not converge		
Levenberg-Marquardt method	456	168	117
Back propagation on-line	2740	2644	2407
Back propagation off-line	did not converge		

Table 1 shows that the second order methods were unstable with the given data. For example, the Fletcher-Powell training method [4] does not converge and the Levenberg-Marquardt method is unstable in the sense that the results and training speed essentially differ for different initial estimates. Back propagation was applied in two ways: off-line and on-line. Off-line training only permitted error reduction to an unacceptable value.
On the other hand, on-line back propagation gives stable results for different initial values of weight matrix. Thus, we conclude that for this problem the on-line back propagation training method is the most effective.

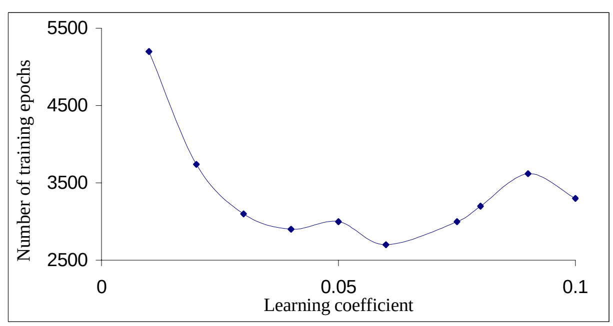

Figure 4. The Number Of Training Epochs For Particular Learning Coefficients In The Range [0,1].

We ran experiments to estimate the best neural network training parameters. Figures 4 and 5 show the results for different learning and moment coefficients. We determined that 0.06 is the best value for the learning coefficients and 0.125 is the best value for the moment coefficients. These values can be used as initial values for training on larger data sets.

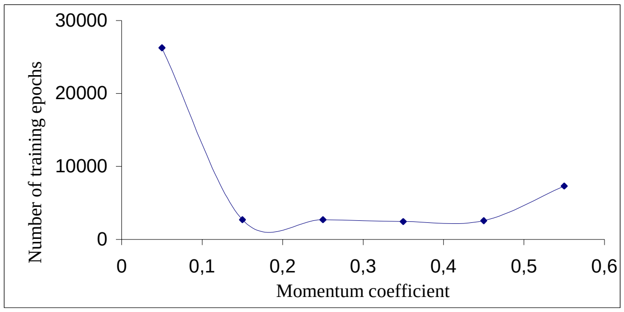

Figure 5. The Number Of Training Epochs For Particular Moment Coefficients.

4. Experimental Results for the Modular NN

The modular neural network that we proposed can be thought of as consisting of two neural networks. Consequently, we discuss the training results of the two subnetworks separately.

4.1. Classifier Training

We considered two variations of a single-layered perceptron for the classifier. The first variation has 2 binary neurons in the output layer with one neuron being assigned to each class (damaged, undamaged). Training precision was set to 0.45. The second variation used a scalar binary output. The network output value corresponds to the undamaged class and 0 to the damaged class. Training precision was also set to 0.45. It took 300 to 400 epochs to train the first variant, but only about 20 epochs (see Figure 6) for the second variant.

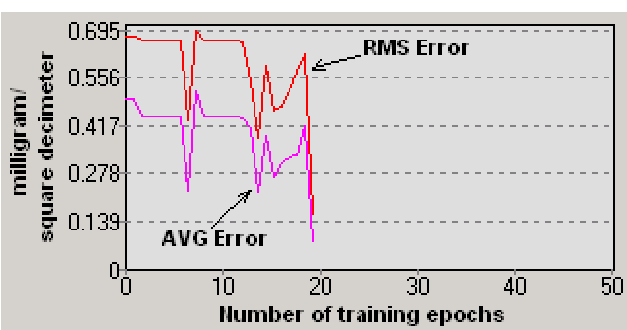

Figure 6. Error As A Function Of Training Epochs For The Scalar Binary Output Classifier.

4.2. Interpolator Training

The output of the classifier divides the input data into two sets. We ran the neural network on nine spectral curves of the type shown in Figure 1. The classifier correctly separated the damaged and undamaged curves, and only the five damaged curves were sent to the interpolator.

The interpolator is a multi-layered neural network. In this case the training set has smaller dimension than that used for the classifier. The results of NN training with a training precision of 0.05 are shown in Figures 7 and 8.

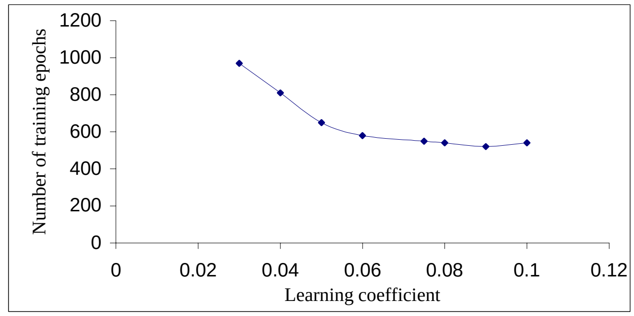

Figure 7. The Number Of Training Epochs For Particular Learning Coefficients In The Range [0,0.12].

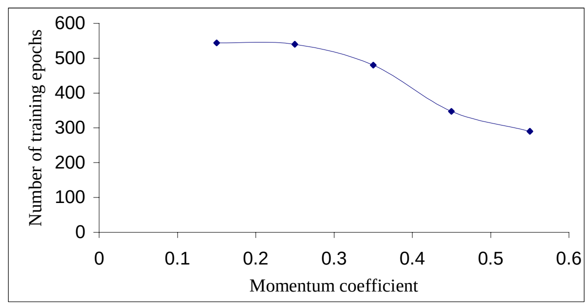

Figure 8. The Number Of Training Epochs For Particular Moment Coefficients.

5. Comparison of Neural Networks

Our experiments show that the modular neural network trains substantially faster than the traditional network. Figure 9 shows the ratio of the number of training epochs iterations for the traditional NN (T) over the number of training iterations for the interpolator (M) in the modular neural network for particular training parameters. It is clear from Figure 9 that the modular NN learns 6-12 times faster than the traditional neural network. Including classifier training will not change the results much because the classifier learns much faster than the interpolator (see Figure 6). The solid-filled bars in Figure 9 show the results based on learning coefficients, while the line-filled bars show the results based on moment coefficients.

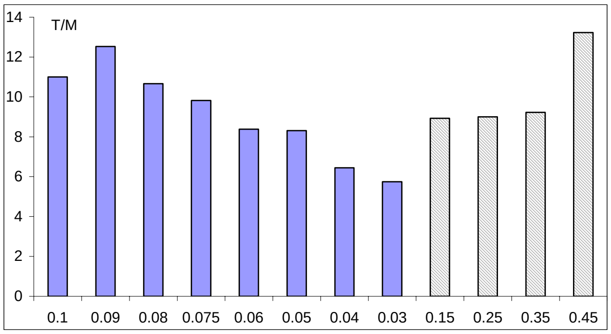

Figure 9. Ratio Of Training Times For The Traditional NN Over The Modular NN For Different Learning And Moment Coefficients.

6. Conclusions

Our experiments confirmed the effectiveness of modular neural networks for determining the chlorophyll content in damaged plants. We expect that increasing the training set dimension would only strengthen our results

We intend to pursue our investigations in two additional directions.

1. We wish to do a more complete chemical analysis of plants based on reflection. A neural network design for doing this is shown in Figure 10.
2. We wish to apply principal component analysis to determine the most best informative features that can be used to reduce the dimension of the input data.

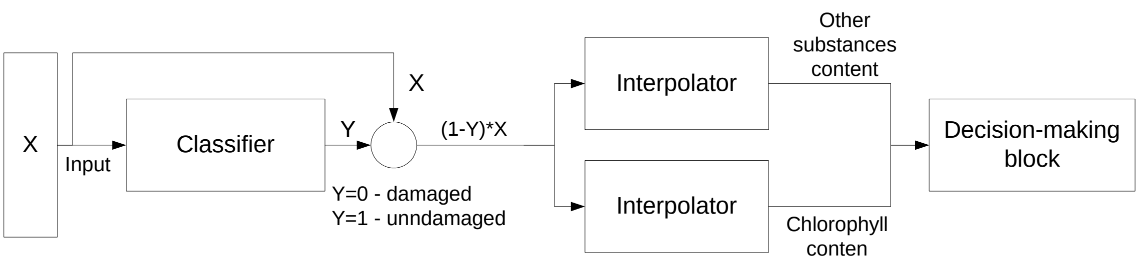

Figure 10 Proposed Modular Architecture Of NN For Extended Analysis Of Plants Chemical Contents.

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