A NEURAL NETWORK APPROACH TO DERIVING OPTICAL PROPERTIES AND DEPTHS OF SHALLOW WATERS

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ABSTRACT

A Neural Network (NN) approach is studied in deriving information of bathymetry for optically shallow waters. In this study, more than 7000 remote-sensing reflectance (ratio of water-leaving radiance to downwelling irradiance above the surface) spectra for shallow waters were created with a semi-analytical model. This synthetic data base covered chlorophyll-a concentrations from 0.2 to 6 mg/m^3, water depths from 0.5 to 20 meters, and dark to bright-sand bottom albedos. The multi-layer NN is trained with the synthetic data using a back-propagation algorithm, and tested with both synthetic and field data. One advantage of using NN approach is that it reduces the calculation time greatly compared to an early optimization method.

INTRODUCTION

Recently, an optimization method has been developed to retrieve bottom depth and in-water properties from measured remote-sensing reflectance[1]. The method is proved accurate and successful, however, it is too slow for image processing using current computers. A quick and reliable method for bathymetry is desired. Over the past several years, more attention have been paid for artificial neural networks (NN) for remote sensing applications[2-7]. For example, Key[8] used the Advanced Very High Resolution Radiometer (AVHRR) data in conjunction with the Scanning Multichannel Microwave Radiometer (SMMR) for the classification of four land surface and eight cloud classes in the Arctic. However, most applications of NN were toward the qualitative classifications of remotely sensed images, few researches were focused on the quantitative derivation of properties of interest. In this study, we investigate the application of using neural networks to derive bottom depth. To design a neural network, large data base is required to well train the neural network, which is not available yet from field measurement, however. Computer models[9,10] are proved that they can generate shallow water spectra, but it is very time consuming. We generate our data base of shallow-water remote sensing reflectance by a semi-analytical model[11], which is simple and easy with high accuracy. We used this synthetic data base to train a neural network, and used both synthetic and field data to test it.

NEURAL NETWORK

A neural network derives its computing power through its massively parallel distributed structure and its ability to learn and therefore to generalize. A neural network is composed of a number of neurons, which are arranged in different network layers and are connected by links. Each link has a numeric weight associated with it. Weights are the primary means of long-term storage in neural networks, and learning usually takes place by updating the weights[12,13]. By back-propagation algorithm[14], each training data is fed to the neural network through input layer; the network output is compared with the desired results; if error is found, the network will iteratively update the weights to reduce the error to an acceptable level.

However, the back-propagation learning algorithm is very slow for many applications, and it scales up poorly as tasks become larger and more complex. Fahlman[15] made several modifications on the original back-propagation algorithm and introduced "quickprop" back-propagation algorithm. The "quickprop" training algorithm is used in this work to train or neural network.

Data Base

As no large filed data available, we used a semi-analytical model (SA-model) to create the training data. The SA-model is,[11]

$$R_{rs} \approx \frac{0.518\, r_{rs}}{1 - 1.562\, r_{rs}}, \tag{1}$$

where r_{rs} (the sub-surface remote-sensing reflectance, ratio of the upwelling radiance to downwelling irradiance evaluated just below the surface) is,

$$r_{rs} \approx r_{rs}^{dp}\left[1 - 1.03 e^{-\left(\frac{1}{\cos(\theta_w)} + D_u^C\right)\kappa H}\right] + 0.31\rho e^{-\left(\frac{1}{\cos(\theta_w)} + D_u^B\right)\kappa H}, \tag{2}$$

and r^{dp}_{rs} (remote-sensing reflectance for optically deep water) is,

$$r_{rs}^{dp} \approx \left(0.070 + 0.155 u^{0.752}\right) u. \tag{3}$$

The path-elongation factors for scattered photons from the water column (D_u^C) and bottom (D_u^B) are

$$D_u^C \approx 1.2(1+2.0u)^{0.5}, \text{ and } D_u^B \approx 1.1(1+4.9u)^{0.5}, \tag{4}$$

with,

$$u = b_b/(a+b_b) \text{ and } \kappa = a+b_b. \tag{5}$$

Where

$$b_b = b_{bw} + b_{bp}, \tag{6}$$

and

$$a = a_w + a_\phi + a_g. \tag{7}$$

Note that it is the combination of Eqs.1-5 to provide the expression for R_{rs}. In Eq.1, 0.518 is the water-to-air divergence factor, and (1-1.562 r_{rs}) accounts for the internal reflection from water to air, which is important for very shallow and/or very turbid waters.

To generate an R_{rs} spectrum from the semi-analytical model, spectra of $a_w(\lambda)$, $a_\phi(\lambda)$, $a_g(\lambda)$, $b_{bw}(\lambda)$, $b_{bp}(\lambda)$, $\rho(\lambda)$ and value of H are required after knowing the solar zenith angle. Values of

$a_w(\lambda)$, the absorption coefficients of pure water, were taken from Pope and Fry[16]. Values for $b_{bw}(\lambda)$ were from Morel[17]. The other variables were modeled as follows:

$$a_\phi(\lambda) = [a_0(\lambda) + a_1(\lambda)\ln(a_\phi(440))]\, a_\phi(440) \text{ (Ref. 11)}; \tag{8}$$

$$a_g(\lambda) = a_g(440)\, e^{-0.015(\lambda-440)} \text{ (Ref. 18)}; \tag{9}$$

$$b_{bp}(\lambda) = b_{bp}(550)\left(\frac{550}{\lambda}\right)^Y ; \tag{10}$$

$$\rho(\lambda) = B * \rho^{mea}(\lambda); \tag{11}$$

where $\rho^{mea}(\lambda)$ is a measured bottom albedo spectrum, with $\rho^{mea}(550) = 0.2$.

Based on the above expressions, we only need to know the values of $a_\phi(440)$, $a_g(440)$, $b_{bp}(550)$, B and Y to create an R_{rs} spectrum. To make the simulated data base more consistent with the variation of natural environment, values of $a_\phi(440)$, $a_g(440)$, $b_{bp}(550)$, B and Y were determined the following way,

$$a_\phi(440) = 0.06\, C^{0.65} \text{ (Ref. 19)}, \tag{12}$$

$$a_g(440) = f * a_\phi(440), \tag{13}$$

$$b_{bp}(550) = 0.02 * 0.3 * g * C^{0.62}, \tag{14}$$

with ranges for C, f, g, B and Y are provided in Table 1.

Table 1. Input values for the generation of R_{rs} data base.

variable	values	description
C	0.2 – 5.4, every 0.6	Chlorophyll a concentration; mg/m^3
f	0.6, 1.35, 2.4	Ratio of $a_g(440)$ to $a_\phi(440)$
g	1, 4, 9	Scaling factor for $b_{bp}(550)$
B	.2, 1, 1.6	Scaling factor for bottom albedo
H	0.5 – 20.0, every 0.5	Bottom depth; m
Y	0.3, 1.0, 1.7	Particle scattering spectral slop

With the above considerations, a set of more than 7000 shallow-water R_{rs} spectra (wavelength from 400 to 700nm every 10nm) were constructed. Part of this data (95%) were used to train a neural network, the rest (5%) were used to test the trained network.

Network Selection and Training

We used a fully connected, feedforward neural network with a multilayer perceptron structure, and trained it by the "quickprop" back-propagation algorithm[15].

The input layer of the network consists of 30 input nodes. The output of the network represents the water depth and is scaled into 0.0 to 1.0 by dividing the maximum value of bottom depth for the training. Other parameters used in the training are left as defaults as those in the "quickprop" algorithm[15]. In the network training phase, inputs from the training data are fed forward through the network. The outputs of the network are compared with target water depth (normalized). The sum square errors (SSE) between the network outputs and the desired outputs are computed and further back-propagated through the network. Weights are adjusted, accordingly, to reduce the SSE. Networks with different configuration (number of hidden neurons and one or two hidden layers) were trained over 7000 shallow-water R_{rs} spectra for 10000 epochs. Each epoch consists of 10 iterations. Through the training, for each network configuration, the weights of the network with the minimum SSE are saved. We started with a one-layer network with 20 hidden neurons and increased the number of neurons and the number of hidden layers.

It was found that a network with one hidden layer and 73 hidden neurons showed minimum sum squared error (SSE) and that this network was chosen as optimum network architecture for this study. Figure 1 shows the evolution of training accuracy in terms of SSE, plotted against the number of epochs. The network's SSE first decreased rapidly with fluctuations through 500 epochs. It stayed stable through epoch 2200 and followed by another series of fluctuations. During the training from epoch 1000 to 2000, the weights of the network with minimum SSE were saved. The network with 73 neurons and the saved weights are regarded as properly trained network and used in the testing and further applications.
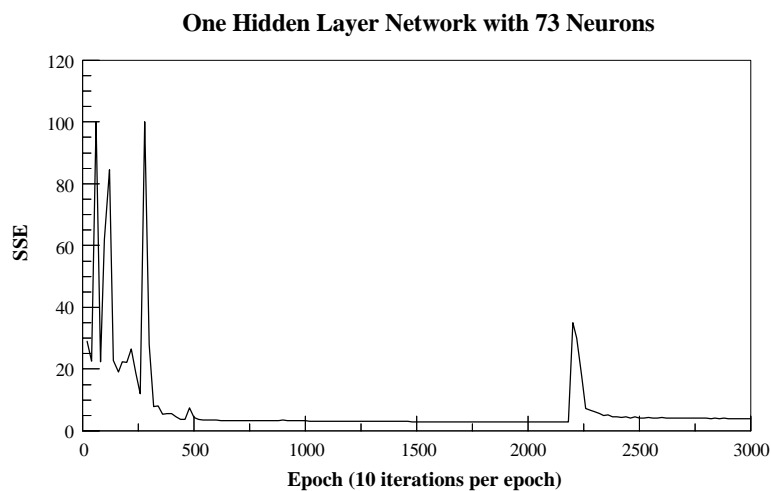
One Hidden Layer Network with 73 Neurons

Figure 1. Taining performance of a one-layer network with 73 hidden neurons.

RESULTS AND DISCUSSION

        The ultimate task of network learning is to apply the knowledge to unseen inputs and to predict outputs of interest. Applying our trained neural network to a set of SA-model created shallow-water R_{rs} (378 points), the average error for depth was about 18% ($R^2 = 0.897$, see Figure 2). Apply this network to a field measured shallow-water R_{rs} data (15 points), the average error for depth was 17% ($R^2 = 0.833$, see Figure 3). These results suggest that the neural network developed here works well in retrieving bottom depth of optically shallow waters, especially when it is desired for image processing. However, due to the limitation of neural network itself, a neural network may perform badly if the input is out of the training boundary. For better and wider applications, a neural network with wider boundary and finer gradient may be required.
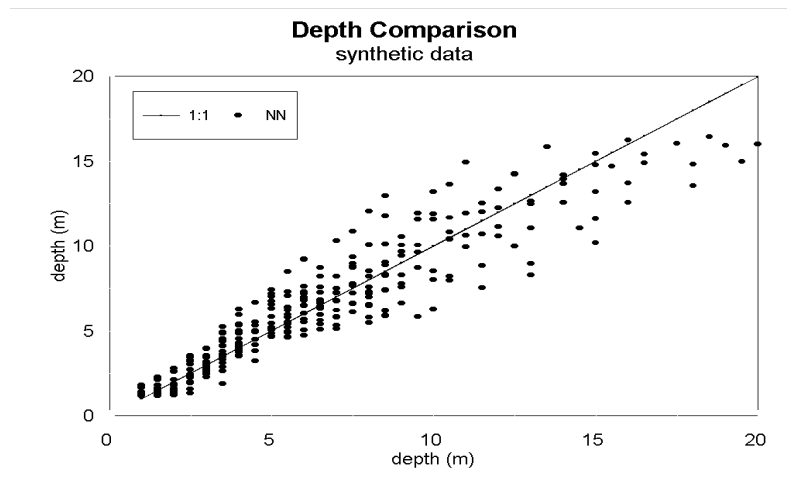

Figure 2. Depth comparison between input and NN output values (synthetic data).
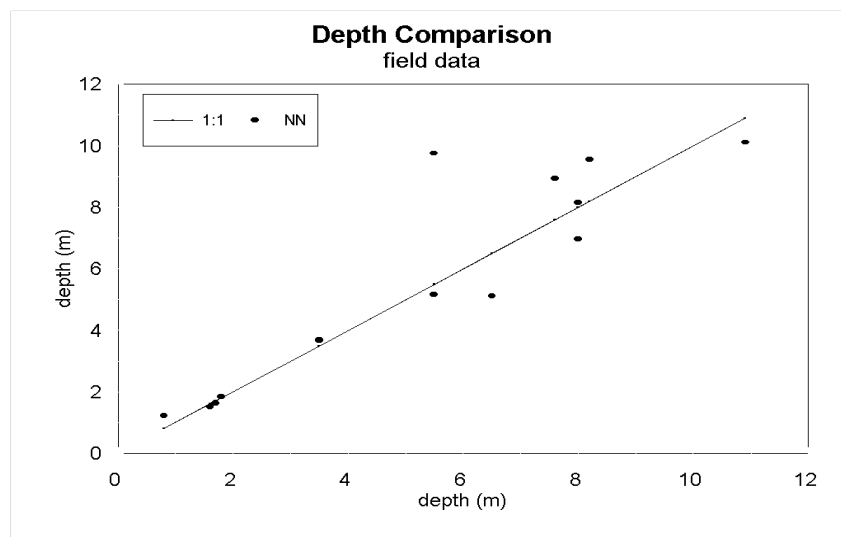

Figure 2. Depth comparison between input and NN output values (field data).

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