Processing Landsat TM data using complex-valued neural networks

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ABSTRACT

Neural networks are massively parallel arrays of simple processing units that can be used for computationally complicated tasks such as image processing. This paper develops an efficient method for processing remote-sensing satellite data using complex valued artificial neurons as an approach to the problems associated with computer vision—region identification and classification—as they are applied to satellite data. Because of the amount of data to be processed and complexity of the tasks required, problems using ANNs arise, specifically, the very long training time required for large ANNs using conventional computers. These problems effectively prevent an average person from performing his own analysis. The solution presented here uses a recently developed complex valued artificial neuron model in this real-world problem. This model was then coded, run and verified on personal computers. Results show the CVN to be an accurate and computationally efficient model.

Keywords: Artificial neural networks, Landsat TM, image processing

1. BACKGROUND

Data by itself is of no real value. For data to be of value, it must first be interpreted. Development of advanced techniques for improving remote sensing image classification accuracy is essential for deriving reliable land cover information for both cultural and natural resource applications. Satellite multispectral data with resolutions down to a small segment of an individual farmer's field are commercially available over the Internet; however, cost effective and user friendly tools for converting data into information are not. Large-scale problems such as this require efficient methods and powerful computers.

An Artificial Neural Network (ANN) is defined by neurons, topological structure, and learning rules. It consists of organized topological interconnections among the processing elements, learning rules, and knowledge recall. The topological structure establishes the frame of the network, the learning paradigm trains the network by presenting example input data pattern and the corresponding desired output, and the recall applies the pattern recognition knowledge learned in the training step to process and in this case classify the raw data. The intelligence of neural networks emerges from the collective behavior of neurons, each of which performs only very limited operation. The most popular forms of neural networks typically consist of three or more layers—an input layer, an output layer, and one or more hidden layers. The input layer consists of one or more processing elements which present the training data, and the output layer consists of one or more processing elements which store the results of the network. Finally, neural networks must be trained prior to use. Training a neural network effectively synthesizes a set of rules from a body of training exemplars. During the training phase, the neural network encodes the necessary transformation, mapping a desired set of input features to specific output features. Applicable training methods are a function of the characteristics of the neural topology and nodal functions.

Neural network paradigms can be divided into two basic categories: supervised learning and unsupervised learning structures. In a supervised learning paradigm, the input data is associated with some output criterion in a one-to-one mapping, with this mapping known *a priori*. The network learns this mapping in the training phase and thus similar inputs are associated with the various desired output classes. The patterns (of known class membership) used to estimate the statistical parameters of each pattern class are usually called a training set. The process by which a training set is used to obtain decision functions is called learning or training. Input vectors may consist of frequency components,

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pixel values, transform coefficients, or any other features considered important. Complex decision regions are typically formed using hyperplane decision boundaries or kernel-function nodes that form overlapping receptive fields. The same principle was applied to the task of region identification accomplished in this project.

Since the mid 1980's there has been a steady growth in the number of applications of neural network algorithms in a wide range of scientific disciplines. The use of neural networks in remote sensing is relatively new; however during the last few years the number of reported applications has been steadily increasing. Porto provides a good summary. [1] Jensen reports that ANNs performed significantly better than traditional methods in modeling stand age due their ability to handle nonnormative data. [2] Benediktsson reports on similar results with multisource data. [3] A majority of applications have used the multi layer perceptron neural network trained with back propagation algorithm although applications employing SOFMs and LVQ methods have also been reported. [4, 5] The sources for these analyses have been a variety of remotely-sensed data including optical high and low resolution multi spectral imagery, data from imaging spectrometers and synthetic aperture radar (SAR).

There are at least four main aspects that should be considered in any NN application: 1) Preparing the data. 2) Designing the network architecture. 3). Estimating the parameters, i.e., training a network for a given problem. 4) Assessing the performances of the network.

In the case of remote sensing data classification, the inputs often represent the vector of brightness values for the multispectral data. [6] Hence, for single-date Landsat-7 TM data, there would be seven input nodes, each corresponding to a band of the Thematic Mapper sensor. A thematic map shows the spatial distribution of identifiable earth surface features; it provides an *informational description* over a given area, rather than a data description. [7] Classifying multisource remote sensing and spatial data requires the ability to match large volumes of input pattern data simultaneously to generate categorical information as output. [8] Since the learning and recall depend on the linear and nonlinear combination of data patterns instead of the statistical parameters of the input data, neural networks offer the opportunity to analyze spatial data with different origins and properties simultaneously, without *a priori* assumptions about the distribution for each data type. In fact, neural networks have the ability to learn those distributions, if they exist, in the input data, which enables the translation of input data into output information. In the present context, this is the land/water region identification corresponding to an input pattern. Ideally, each data type will make a unique contribution to the discrimination of feature class patterns, therefore, enabling the neural network to learn the spectral, spatial, and temporal signature of each class. [9]

The use of complex valued neural networks in this field is however in its budding stage. Various researchers have developed complex-valued ANNs and applied them to complex-valued data, such as complex signals and Fourier transform. [10, 11, 12, 13, 14, 15, 16] Others have explored optics in the course of finding a suitable candidate for implementation of neural networks, which naturally perform calculations in the complex domain. [17, 18, 19] Complex numbers have also been exploited for Hopfield type associative memory for associative retrieval with partial input [20, 21] and for rotation invariant retrieval using Fourier transform of edge data. [22] Still others have developed complex-valued artificial neural networks to solve Boolean logic functions of n variables by selecting an output state from a complex plane divided into m regions, with $m > n$. [23]

The work proposed here extends complex numbers for general ANN. It is shown that representing real world digitized scalar data as phase and operating on this data in the complex-domain improves the performance of ANNs. The representation of the new neuron is shown to be at least as computationally powerful as, and in many cases more powerful than existing ANNs. In earlier works, Michel and Awwal have shown the equivalence between a phase-encoded complex valued neuron and the phase-only filter. [24, 25]

This paper illustrates the use of complex valued neurons for an improved classification of satellite images. Water and land region identification in a multispectral landsat TM image has been carried using the complex valued neurons and the advantages of this method over conventional methods have been evaluated.

The objective of this research was to develop an efficient and cost effective method for processing satellite data on small, commonly available computers such as PCs or workstations. The path of this objective included: the development of a new complex valued ANN model suitable for implementation on these types of machines, obtaining and processing actual satellite data, both with traditional methods and the new method, verifying the correctness of the new method, and analyzing the improvement of the new method over traditional ANN solutions to specific real-world problems. These steps are discussed below.

2. COMPLEX VALUED NEURON ARCHITECTURE

In developing the complex valued neuron, new representations for input data, intermediate data, output data and internal weights, along with the input, aggregation, activation, and output mappings were derived. Specifically, the model of a simple-perceptron like Complex Valued Neuron (CVN) using a phase encoding of real-valued input-data and complex-valued weights is used.[26, 27] For completeness, these results are summarized below.

In the complex neuron, all weights are represented by complex numbers. Weights are represented as shown in equation 1. Each weight has two independent components, a magnitude, λ_w, and a phase, θ. For purposes of the work presented here, the magnitude of each w_i has been set to a constant value of 1. Therefore, the effective portion of the weight term is only the angle component.

$$w_i = \lambda_{wi} e^{i\theta_i} \tag{1}$$

The input mapping represents how the real-world data is represented in the ANN calculations; that is, it defines input data-set P. In the complex neuron, this mapping was from a real-world value—typically the pixel values—into a complex number. Thus every input had a magnitude and an angle. A linear mapping to represent the inputs was chosen as shown in equation 2, such that input data mapped to the range of 0 to $\pi/2$. As in the weight terms, the magnitude has been set to a constant value of 1. Therefore, the effective portion of the input components are only the angle components. Red, blue and green components have been used to form a color image out of the first three bands of Landsat 7 data. Thus in the image used, each color appears in its primary spectral components of red, green and blue and each pixel is characterized by three values. The concept of thresholding was one of finding clusters of points in 3-D space. The image was segmented by assigning one intensity to pixels whose RGB components are closer to one cluster and another intensity to the other pixels in the image.

$$p_i = \exp\left(i \frac{\text{value}}{\text{Max Value}} \frac{\pi}{2} \right) \tag{2}$$

The aggregation function (equation 3) was designed after the traditional neuron's aggregation function, that is, a weighted summation. Where **P** is a column vector of the input components p_i and **W** is a row vector of weight terms w_i.

$$q = \mathbf{WP} \tag{3}$$

The activation function or thresholding function operates in the intermediate space ("q-space"). It provides a non-linear stage that allows traditional artificial neurons to be cascaded, thus increasing their computational power. The activation function used in this project was perceptron like, that is a hard limiting function, but the domain of the complex valued activation function was the magnitude of the values in the intermediate space. The activation function was expressed as shown in equation 4 where a and T are real numbers, and q is complex.

The change in output in response to a weight change depends on the relationship of that weight to the other weights and all inputs. A weight term is not simply associated with only its corresponding input.

$$a = \begin{cases} 0 \text{ if } |\text{q}| < \text{T} \\ 1 \text{ if } |\text{q}| \geq \text{T} \end{cases} \tag{4}$$

Assume that the weight change is $\Delta w = w_{\text{new}} - w_{\text{old}}$. The relevant part of the weight term is its angle, θ, therefore, $\Delta w = \Delta\theta = \theta_{\text{new}} - \theta_{\text{old}}$. Equation 5 is thus selected as the training rule for the complex-valued neuron. The proportionality constant, η, is also known as the "learning" rate. The error $d - a$, (desired – actual) is known, and $r = q^2$.

$$\theta_{i\,\text{new}} = \theta_{i\,\text{old}} + \eta(d - a)\frac{1}{\frac{\delta r}{\delta\theta_1}} \tag{5}$$

Benefits arise from using the CVN because the complex-valued representation will be computationally more powerful than the existing representations. For example, a single complex-valued neuron constructed using the new representation can solve problems that are not linearly separable. Conventional neurons require at least two layers to solve this problem; therefore, ANNs can be constructed with fewer artificial neurons. Although each individual neuron will be more complex, the overall ANN will require less hardware or use fewer mathematical operations to solve existing problems, therefore, speed of operation will be increased and cost will be lowered. These expected benefits are implementation dependent.

3. APPROACH

This work may be treated as one of the common computer vision tasks of region identification accomplished in a novel manner—that is, with a complex-valued neuron. Often, region segmentation in a digital image is done by traditional computer vision methods such as thresholding, wherein threshold level of some criteria-often brightness is selected. Pixels above that threshold are assigned to one region and pixels below that are classified into another region. Methods of selecting an appropriate threshold vary but often involve calculating a histogram of brightness levels and selecting a value that will divide the histogram into two 'natural' areas. The assumption being made here is that the natural division of the histogram—if there is one—is reflective of the desired classification of the picture regions. Additionally the picture is often smoothed, or filtered to remove pixel level noise before processing by methods like principal component analysis. The digital satellite image for classification chosen in this project is the picture consisting of bands 1 2 and 3 in red, blue and green respectively of the Boston region of New England from a Landsat-7 TM data. The size of the image is 700 by 900 pixels. With this representation, the eye can readily see the water region in the image, yet it is a common computer vision task requiring a moderate amount of processing—smoothing, calculating a histogram, selecting a threshold, and applying the threshold pixel by pixel—to accomplish.

The neuron was trained with 18 9-tuple inputs, nine inputs representing water and nine representing land. These 18 inputs were selected by identifying two differently colored windows in the image, one representing water and one representing land. Each window thus provided nine, non-overlapping, 3-pixel by 3-pixel samples or nine 9-tuples from either water or land on which to train the complex neuron. The individual elements of the 9-tuples were comprised of three values, one for each of the three TM bands selected. These data ranged continuously from 0 to 255. A linear mapping to represent the training sets was chosen as shown in equation 2 such that these RBG data mapped to the range of 0 to $\pi/2$.

An appropriate goal was associated with each input 9-tuple. That is input patterns from the water region were associated with a positive result (desired output = 1) and those that were not water were associated with a negative result (desired output = 0). The net was trained until post-threshold error was zero and the learned weights had the ability to detect the desired region from the actual image. After training, all 3 by 3 windows of the image were processed through the complex neuron thus behaving as the test patterns to the network. The neuron then responded positively or negatively to each window. The detected regions were recoded with different pixel values each for land and water.

4. RESULTS

An ideal neural network learning approach was employed. A small region representing land and one representing water was picked from the actual dataset and fed to the neuron as input. The training was carried out until post threshold error was zero. The number of iterations for each training was noted and the learned weights were used to test the network. Then the entire image was fed to the neuron for identification of land or water regions. It was noted that an increase in the training time gave improved results in identifying some regions that looked like water (In the raw image, these regions were colored differently from actual water because the water in these regions was perhaps not very deep). Comparison of the raw unprocessed image with the computer output reveals identification results that extremely accurate. Figure 1 shows the image after neural net processing for land and water region identification.

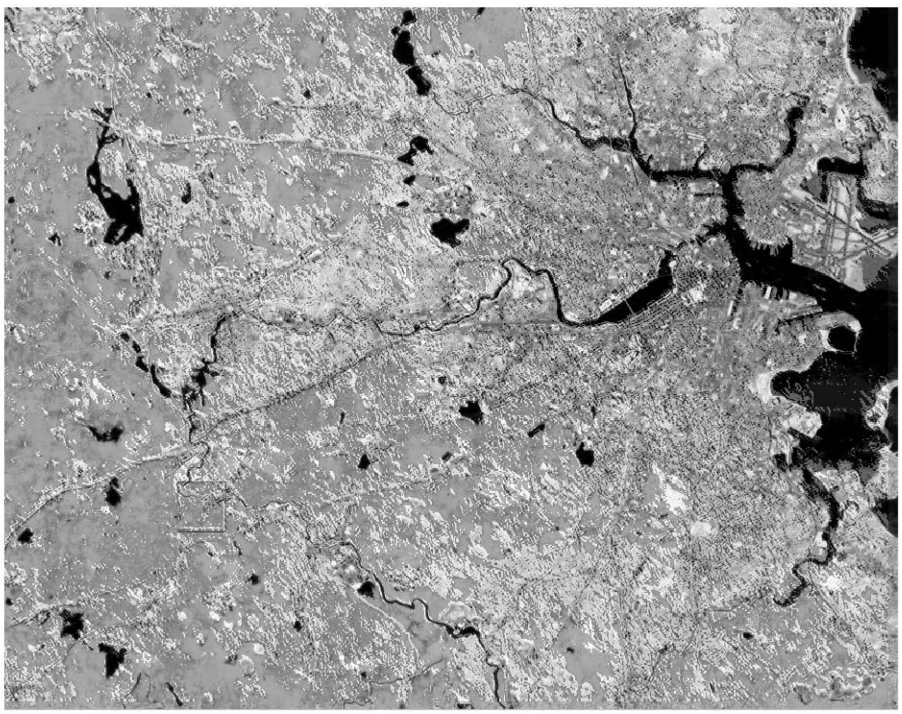

Figure 1 Satellite image after processing for identification of land and water

Clearly the complex neuron segmented the image into 2 regions—land and water. A similar segmentation was accomplished for rural land and roads region identification.,

When the same training set was used to train an artificial neural net classifier using a commercial product, it often identified the roads as water. Many of the other common algorithms like minimum distance classifier, Mahalanobis classifier, isodata classifier and k-means classifier classified the roads as water when trained with just one training set each for land and water. The complex valued neuron needed only one set to identify the regions perfectly. It was noted that the other conventional classifiers would perform very well if many more training sets were used.

An important term for performance evaluation of classifiers is error. Simply, an error is a misclassification: the classifier is presented a case, and it classifies the case incorrectly. If all errors are of equal importance, a single-error rate (error rate = number of errors/number of examples), summarizes the overall performance of a classifier. However, for many applications like the problem of interest, distinctions among different types of errors turn out to be important. For example, the error committed in predicting a food as safe for consumption when it is actually poisoned (known as a false negative decision) is usually considered far more serious than the opposite type of error-of predicting the food as poisoned when it is in fact safe for consumption (known as a false positive).

If distinguishing among error types is important, then a *confusion matrix* can be used to lay out the different errors. Table 1 is an example of such a matrix for three classes.

	True class		
Predicted class	Water	Land	Roads
Water	10	1	0
Land	1	10	0
Roads	0	2	9

Table 1: Confusion matrix for 3 classes land, water and roads.

The confusion matrix lists the correct classification against the predicted classification for each class. The number of correct predictions for each class falls along the diagonal of the matrix. All other numbers are the number of errors for a particular type of misclassification error. For example, class water in Table 1 is correctly classified 10 times, but is erroneously classified as class land 1 time(s). Class roads is correctly classified 9 times but incorrectly classified as land 2 times. Two-class classification problems are most common, since multi-class problems can also be represented as a series of two-class problems. With just two classes, the choices are structured to predict the occurrence or non-occurrence of a single event or hypothesis (presence of class water/land and/or roads/land in the image). In this situation, the two possible errors are frequently given the names mentioned earlier from the food prediction example: false positives or false negatives. Table 2 lists the four possibilities, where a specific prediction rule is invoked.

	Class Positive (C+)	Class Negative (C-)
Prediction Positive (R+)	True Positives (TP)	False Positives (FP)
Prediction Negative (R-)	False Negatives (FN)	True Negatives (TN)

Table 2: Confusion matrix for a two-class classification problem

Table 3 is a specific confusion matrix for the land/water classification problem and table 4 is the specific confusion matrix for the land/roads classification problem.

	10 (C+)	10 (C-)
10 (R+)	10 (TP)	0 (FP)
10 (R-)	1 (FN)	10 (TN)

Table 3: Confusion matrix for land and water classification problem

	10 (C+)	10 (C-)
10 (R+)	9 (TP)	0 (FP)
10 (R-)	2 (FN)	10 (TN)

Table 4: confusion matrix for land and roads classification problem

A classic metric for reporting performance of machine learning algorithms is predictive accuracy. Accuracy reflects the overall correctness of the classifier and the overall error rate is (1 - accuracy). If both types of errors, i.e., false positives and false negatives, are not treated equally, a more detailed breakdown of the other error rates becomes necessary. Accuracy has many disadvantages as a measure. Its basic shortcomings are that it ignores differences between error type, and it is strongly dependent on the class distribution (prevalence) in the dataset rather than the characteristics of examples. In the evaluation of information retrieval systems, the most widely used performance measures are *recall* and *precision*. *Recall and precision* are mostly utilized in situations where *TP* is small when compared with *TN*

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} = \mathrm{Senstivity} \tag{7}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{6}$$

	Land/water Problem	Land/roads problem
Recall	.909	.818
Precision	1	1

Table 5: Recall and precision values for the CVN in identifying land, water and roads regions in the satellite image.

Sensitivity	TP / C+
Specificity	TN / C-
Predictive value (+)	TP / R+
Predictive value (-)	TN / R-
Accuracy	(TP + TN) / ((C+) + (C-))

Table 6: Formal measures of classification performance

	Land/water classes	Land/Roads classes
Sensitivity	1	.90
Specificity	1	1
Predictive Value (+)	1	1
Predictive Value (-)	1	1
Accuracy	1	.95

Table 7: Formal measures of classification performance of the complex valued neuron in identifying land, water and roads regions in the satellite image.

It is noted that the accuracy of the CVN in identifying the regions of interest in the satellite image is 97.5% for the samples considered. This is an average value of the accuracies obtained from the CVN for both land/water region identification and land/roads region identification in the satellite

5. CONCLUSION

It was observed that, compared to conventional calculation and statistics based classification of satellite images, the application of complex valued neuron to remote sensing data processing is in its infancy. The complex valued neuron has the ability to handle remote sensing data without prior assumptions or considerations about the distribution of feature classes and measurement scales of those data. The complex valued neuron was found to be more accurate than a traditional artificial neuron and other conventional classification methods considering the number of training sets required for learning and the time taken for processing when identifying the land, water and roads regions in a satellite image.

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