Remotely Sensed Change Detection Based on Artificial Neural Networks

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Abstract
A new method for remotely sensed change detection based on artificial neural networks is presented. The algorithm for an automated land-cover change-detection system was developed and implemented based on the current neural network techniques for multispectral image classification. The suitability of application of neural networks in change detection and its related network design considerations unique to change detection were first investigated. A neural-network-based change-detection system using the backpropagation training algorithm was then developed. The trained four-layered neural network was able to provide complete categorical information about the nature of changes and detect land-cover changes with an overall accuracy of 95.6 percent for a four-class (i.e., 16 change classes) classification scheme. Using the same training data, a maximum-likelihood supervised classification produced an accuracy of 86.5 percent. The experimental results using multitemporal Landsat Thematic Mapper imagery of Wilmington, North Carolina are provided. Findings of this study demonstrated the potential and advantages of using neural network in multitemporal change analysis.

Introduction
Global environmental change has become a major national and international policy issue. Not only does change alter the local landscape, but it may also produce ecosystem effects at some distance from the source (Dai and Khorram, 1998a). While a considerable amount of data about the nature of the Earth's surface has been collected by remote sensing devices, the volume and rate of these data are expected to increase rapidly as more images of various resolutions become available in the public domain, such as Earth Observing System (EOS) data (Asrar and Greenstone, 1995). These remotely sensed data are used to determine land use and land cover at a given point in time and land-cover changes between multiple dates (Miller *et al.*, 1995). Given the current techniques available, remote sensing provides one of the most feasible approaches to local, regional, and global land-cover change detection (Khorram *et al.*, 1999).

Many change-detection techniques are used in practice today. Most techniques are semi-automated because analysts still have to manually carry out many image processing tasks such as image registration, threshold tuning, and change delineation. There are also problems associated with semi-automated techniques, including being time-consuming, inconsistent, and difficult to apply to large-scale and global information systems, such as the International Earth Observing System (IEOS) (Dai and Khorram, 1998b). Additionally, a number of the techniques can only provide a binary change mask, and a classification procedure must be applied to the multitemporal images to extract categorical change information (Serpico and Bruzzone, 1997; Coppin and Bauer, 1996; Singh, 1989). Therefore, a reliable automated change-detection system identifying categorical changes would be useful in environmental remote sensing and its regional or global implementation. This paper reports the development of procedures for such a change detection system based on artificial neural networks.

This paper includes five sections. An overview of remotely sensed change detection is first presented. Experimental design of the proposed neural-network-based change-detection system is then discussed, which includes the network input, output, and architecture, along with fundamentals of the backpropagation training procedure. The experimental results are then presented, where we focus on the classification scheme, training data development, network parameter selection, generalization problems, change detection accuracy assessment, and comparison with other techniques of categorical change detection. Finally, conclusions and recommendations are given.

Remotely Sensed Change Detection
Usually, change detection involves two or more registered remotely sensed images acquired for the same ground area at different times. During the last two decades, there have been many new developments in remotely sensed change detection. These techniques may be characterized by their functionalities and the data transformation procedures involved. Based on these characteristics, we can classify current change-detection techniques into two broad categories:

- Change Mask Development (CMD): Only changes and non-changes are detected and no categorical change information can be directly provided; and
- Categorical Change Extraction (CCE): Complete categorical changes are extracted.

In the first category, changed and non-changed areas are separated by a preset threshold when comparing the spectral reflectance values of multitemporal satellite images. The amount of change is a function of the preset threshold. The threshold has to be determined by experiments. The nature of the changes is unknown directly from these techniques and needs to be identified by other pattern-recognition techniques. Therefore, these techniques are only suitable for development of a change mask. Most change-detection methods fall into the first category. For example, *Image Differencing, Image Ratioing*, and *Image Regression* only lead to the development of a change mask. These techniques can be used for data of one band, two bands, three bands, or more than three bands, with decision

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boundaries which are two-threshold, elliptical, ellipsoidal, or hyper-ellipsoidal, respectively. The data used can be spectral data or data transformed by various linear or nonlinear transformations, such as vegetation indices (e.g., Normalized Difference Vegetation Index (NDVI) and Tasselled Cap Transformation) (Lambin and Ehrlich, 1996). Other linear transformations include the multispectral Kauth-Thomas transformation (MKT), Gramm-Schmidt orthogonalization (GS), and multidate principal component analysis (PCA) (Byrne *et al.*, 1980; Baronti *et al.*, 1994; Collins and Woodcock, 1996).

The CMD techniques in the first category usually can not identify what land-cover changes have taken place in the area of interest. In CCE, however, the explicit categorical changes are detected directly based on the spectral reflectance of the data. There are mainly three techniques in this category: *Change Vector Analysis, Post-Classification Comparison*, and *Direct Multidate Classification*. In Change Vector Analysis, the magnitude of the change vector represents the degree of change, while the direction of the change vector indicates the type of change with the help of supervision (Malila, 1980; Michalek *et al.*, 1993). This method is computationallyexpensive because the data have to be geometrically corrected and digitally merged; then transformation coefficients have to be developed, and finally spectral/spatial clustering is done. Also, the performance of the procedure is sensitive to its parameter setting. Post-Classification Comparison simply classifies each of two images acquired at two different times and compares the classified maps on a pixel-by-pixel basis to identify the changes. The performance of this technique critically depends on the accuracies of the individual classifications because it does not take into consideration the dependence between the two images. The accuracy of this technique tends to be the product of the two independent classifications, which greatly reduces the final accuracy of the change detection (Coppin and Bauer, 1996). In contrast, Direct Multidate Classification deals simultaneously with the two multispectral images acquired at two different times. This method is based on a single analysis of a combined data set of two or more dates to identify changes. Each change combination between the two times is represented as an output class, and the change-detection process is treated as one classification. However, to efficiently use this technique and obtain training statistics, such as the probabilities of transitions for each change combination, one has to develop a set of training data in which each pair of training sites corresponds to the same ground location in the two images (Bruzzone and Serpico, 1997).

In summary, there are five problems associated with current change-detection techniques. First, only very limited information or no information at all about the direction and characteristics of actual changes (*i.e.*, "from-to" information) occurring on the ground can be deduced using most current change-detection techniques. The post-classification technique provides "from-to" information, but it involves two separate image classifications, which causes the change error to accumulate and its accuracy to suffer. Second, while the amount of change detected is one of the most important objectives in change-detection applications, most of the current methods need a user-specified threshold to determine the amount of change. The threshold is often set empirically because there is no theoretical guidance to this problem. Third, most techniques are not fully automated and some are not quantitative. For example, the *Write-Function Memory Insertion* method (Singh, 1989) is basically a visual demonstration technique. Fourth, in some change-detection techniques, such as post classification, the dependency of information between the two images is ignored. Finally, it is challenging in practice to use the direct multidate classification technique due to its characteristics, such as the preference for accurate estimation of transitional probabilities of changes.

To explore the solutions to the problems associated with current change-detection techniques, we investigate the use of neural networks in a change-detection system. Neural networks represent a fundamentally different approach to statistical pattern recognition, because they do not rely on statistical relationships (Bischof *et al.*, 1992). Instead, neural networks adaptively estimate continuous functions from data without specifying how outputs depend on inputs statistically. In past decades, the artificial neural network, or multi-layer perceptron (MLP), has been developed and applied to general pattern-recognition problems (Schurmann, 1996). Research on the use of neural networks in classification of remotely sensed imagery started about a decade ago. Researchers have found that the neural network approach is a promising avenue for classification of remotely sensed imagery (Hara *et al.*, 1994; Heermann and Khazenie, 1992).

In remote sensing, neural networks have been applied to both monosource image classification (Dreye, 1993) and multisource data classification (Benediktsson *et al.*, 1990). Most researchers concluded that the neural-network-based method improved the classification accuracy in comparison with the benchmark method: the maximum-likelihood classifier (MLC). When the data distributions are strongly non-Gaussian, the neural network classifiers are preferable because the assumption of Gaussian distribution in the MLC is no longer satisfied (Paola and Schowengerdt, 1995a). The advantages of the neural network method would be beneficial to change detection because of the complexity of data types in change detection (multisource and multitemporal) (Dai *et al.*, 1998). Change detection is different from multisource classification (including using multitemporal imagery) in that extraction of changes, including the cover types at both times, is the objective, and the results are basically composed of two classification maps. Change detection can also be thought of as a form of image classification which uses multidate and multispectral imagery as its input. Therefore, the principles of neural-network-based classification can be applied to change detection.

A neural network has been used in real-time target detection using synthetic aperture radar (SAR) images (Oliver and White, 1990). Two major difficulties associated with SAR image change detection were identified by White (1991): the removal of speckle noise and the registration of images. In this study, a neural network was trained to understand speckle noise removal. Based on the object features extracted by automated image understanding systems, a neural network was used to discriminate changed features of human-made objects and structures (Uberbacher *et al.*, 1996). In addition to target detection applications, artificial neural networks have also been found useful in remotely sensed change detection. A neural network was trained to combine the different change measures at a parcel level, including structure measures (*e.g.*, edges, corners, and texture), in order to identify changes and no-changes (Rosin, 1994). A method for change-mask development was proposed by Chen *et al.* (1995) using a neural network for determining the change and no-change classes directly based on the image gray levels. Artificial neural networks were used to estimate the quantitative change (mortality) in one category of land cover (conifer) (Gopal and Woodcock, 1996). These previous studies all contributed to change detection using neural networks; however, they were limited to either change-mask development or single-class change quantification. Given the practical demand for categorical land-cover change detection, it is interesting and worthwhile to explore the neural network approach to automated change detection identifying categorical land-cover transitions.

The objectives of this research are to test the capability of artificial neural networks in land-cover change detection and to investigate the major procedures for developing a neural-network-based change-detection system from selection of input data to final assignment of change classes. We approach these objectives by emphasizing several important processes, including training data development, change output encoding, and training using the backpropagation algorithm. Particular emphasis is also given to both the unique problems and characteristics of the neural network method as compared to conventional change detection methods such as the commonly used Post-Classification Comparison.

Methods and Data Sets

The network design of a neural-network-based land cover change-detection system considers both architectural and parameter selections. Architectural considerations include the selection of the network type and the configuration of the network. Parameter selections define the way in which the network operates within the architectural context. They include design aspects such as the format of the inputs and outputs, learning rule and learning schedule, and the data presentation decisions, such as composition of the training file and range used for normalizing the data. In the following, we investigate the basic architectural elements of a neural-network-based land cover change-detection system: network input, network output, network architecture, and network training parameters and procedures.

Network Input

The input data for change detection consist of two registered images of the same area acquired at different times (usually anniversary dates). For multitemporal and multispectral remotely sensed data, the favored input structure is to read one multitemporal and multispectral pixel into the network at a time (Liu and Xiao, 1991). As in most statistical classifiers, the pixels of the whole image are fed into the network sequentially on a pixel-by-pixel basis. In this case, each input node is used to represent the data for one spectral band. If only the nonthermal TM bands are used, 12 input nodes are required. To incorporate other information, additional input nodes can be added and different input schemes might be used. For example, in order to introduce texture information into the training procedure, all bands of the pixels in a 3 by 3 window are used as the input (Paola and Schowengerdt, 1995b). The input structure of a neural network makes it easy to add additional sources of data to the change-detection procedure by simply adding input nodes. This makes neural-network-based change detection attractive when fusion of optical, radar, and other ancillary data is necessary. For fully connected neural networks, the presenting order of the input data must be consistent. The neural network algorithms are often designed to take input data ranging from 0 to 1 to avoid the use of a scale when the sigmoid activation function is evaluated and to reduce floating point computations (Paola and Schowengerdt, 1995a). Therefore, it is important to scale the value of each pixel to this range, and to present the scaled values to the input nodes.

Network Output

Change Output Encoding

Due to the large number of change combinations in change detection, the output encoding for a land cover change-detection system is a challenging task. There are k^2 change combinations for a k-class classification scheme. One solution to reduce the number of outputs is to use binary encoding. In this method, only $2\log_2 k$ output nodes are required to represent k^2 change classes. A single output node has also been used to further reduce the number of output nodes (Civco, 1993). In Gopal and Woodcock (1996), one output node was used to represent the continuous change of conifer mortality. However, one output node usually has limited capability to identify a large combination of output classes. This output encoding scheme is also subject to convergence problems because the network is required to converge at more than one output value. The natural way to encode the output classes is to use one output node per ground cover change class, a method called direct encoding. Based on our experience, for a classification with less than five classes, *i.e.*, 25 change classes, we recommend using direct encoding. For a classification with more than five classes, use of the binary encoding or another efficient output node reduction technique is needed.

Extraction of Change Classes

In direct encoding, every output node represents one change class and each node is trained to have a high value if the input pixel belongs to that class. After the network is trained, the output values of the network are continuous and need to be coded to represent the final change classes. There are two ways to code the continuous output values to extract class labels. The first is to interpret the continuous output values as a measure of class mixing and code them as a membership value in a particular change class. The membership interpretation using fuzzy logic leads to detection of mixed pixels (Key *et al.*, 1989). The second is to characterize the output values as a measure of classification confidence. The higher the output value, the higher the confidence that the pixel belongs to that particular class. Therefore, the class label of the input pixel can be coded as the class corresponding to the output node with maximal output value. This is the simplest way to assign a change class to the input pixel.

Network Training: Backpropagation Algorithm

The network in this study was trained using the backpropagation algorithm, a supervised learning algorithm that requires a series of input-output pairs as the training set. The process of training may be thought of as a search in the network parameter space guided by an additive error function of statistically independent examples which measures the quality of the network's approximation to the input-output relation. The objectives of network training are to minimize the error for all possible examples and to generalize outside of the training set.

The backpropagation algorithm was initially developed by Rumelhart *et al.* (1986). It has two phases: a forward phase and a backpropagation phase. The output values of the network are determined by the forward phase and learning is performed in the backpropagation phase. In the forward phase, the outputs of each layer are transmitted to the nodes in the successive layer. In the backpropagation phase, learning is performed using supervised gradient decent learning algorithms. The learning algorithm iteratively adjusts the weights of the connections in the network in order to minimize a continuous differentiable error function between the actual and desired outputs. The weights are adjusted by taking incremental changes: i.e.,

$$\Delta w = -\eta \frac{\partial E}{\partial w} \tag{1}$$

where E is the square of errors between the desired outputs and actual outputs; η, the learning rate, is the percentage of the step taken towards the minimum error in each iteration. The method of adaptive learning rates can be used to reduce training time and ensure stability at the same time (Jacobs, 1988). To avoid the network spending a lot of time going back and forth between training examples while learning, different method of averaging can be used instead of batch learning. Rumelhart *et al.* (1986) suggested modifying Equation 1 by adding a momentum term as follows:

$$\Delta w(n+1) = -\eta \frac{\partial E}{\partial w} + \alpha \, \Delta w(n) \tag{2}$$

where $\Delta w(n+1)$ and $\Delta w(n)$ are the weight changes at step $(n+1)$ and step n, respectively, and α is the momentum. Rather than averaging the derivatives, momentum averages the weight changes themselves (Smith, 1993). Used in conjunction with example-based learning, momentum speeds the reduction in the error with less computation.

Network Architecture

The numbers of necessary inputs and outputs, and the structure of the first and last layers of the neural network, are often fixed after the determination of input data types and output data structure. However, the number of hidden layers and their size must be determined experimentally. More hidden layer nodes give the network more flexibility in partitioning the decision space. Generally, for classification of multispectral imagery, a three-layer fully interconnected network is sufficient and is the most common implementation seen in the literature (Paola and Schowengerdt, 1995b). For more complex problems, such as change detection with large change combinations, the arbitrary decision capabilities of a four-layer network may be required in order to achieve an accurate classification. Therefore, a four-layer network was used in these experiments.

The architecture of the four-layer network considered in this research is shown in Figure 1. In this diagram, the input data are the two registered Landsat Thematic Mapper (TM) images of the same area. The number of the input nodes is determined by the number of TM bands used in the change detection. The number of output nodes is decided by the number of ground-cover classes and the output encoding scheme. For direct encoding, k^2 output nodes are required to accommodate a k-class application. The network parameters such as the learning rate and momentum, the termination rule, and the number of nodes in each hidden layer are determined by experiments.

Data Sets

The image data used to develop and test the neural-network-based land cover change-detection system correspond to the surroundings of Wilmington, North Carolina with flat topography. Two Landsat TM images of this area were used: one collected on 24 November 1988 (T_b) and the other on 26 December 1994 (T_{b+1}). The six nonthermal TM spectral bands used in the change detection were blue (TM band 1), green (TM band 2), red (TM band 3), and three infrared bands (TM bands 4, 5, and 7). Therefore, the neural network has 12 input nodes. Each pixel in the image corresponds to a ground cell 28.5 by 28.5 *m* in size. The Winter 1988 scene and Winter 1994 scene have been registered to each other with a quarter pixel accuracy. A 512 by 512 subscene of the six nonthermal bands was used for land cover change-detection experiments.

Results

Classification Scheme

The desired output was a classified change map based on a variation of the standard land-use/land-cover classification scheme proposed in Anderson *et al.* (1976). The present scheme differs from the Anderson Type I scheme in that the classifications in this study exclude snow and tundra and combine agricultural and urban land into a single category. The final classes are (1) forest, (2) agriculture/bare/urban (ABU), (3) cypress/wet deciduous scrub/marsh (CWM), and (4) water. The reasons for using this classification scheme in the experiments include (1) the classification logic should be unambiguous; (2) the classes should be remotely sensible, maximizing between-class variations and minimizing within-class variations; and (3) further distinction should be facilitated based on the classification results.

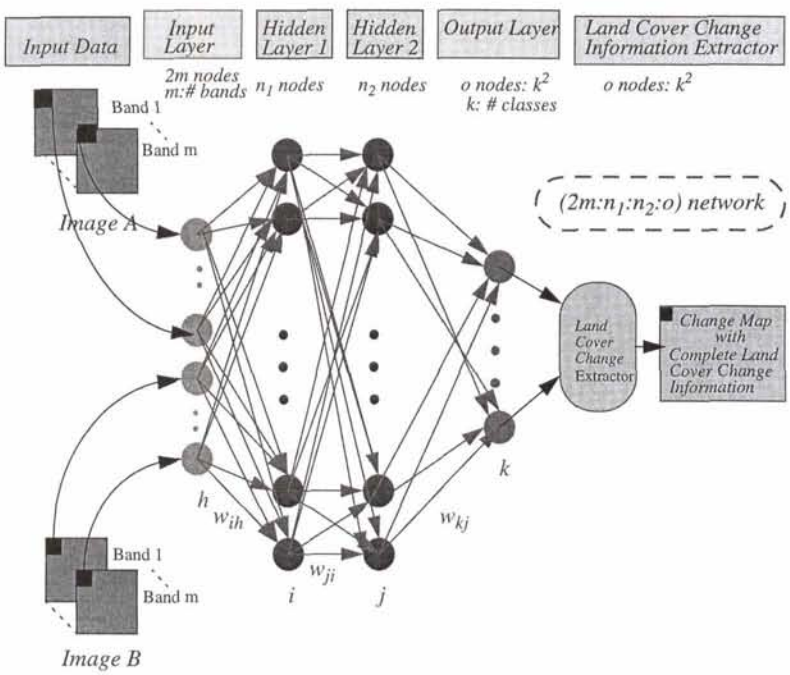

Figure 1. Neural network architecture for a change detection system. This four-layer neural network includes an input layer with ($2m$) input nodes, two hidden layers with n_1 and n_2 nodes, respectively, and one output layer with k^2 output nodes for a k-class classification scheme.

Each class or each land-cover change combination has a value in the output portion of the data vector. The output coding scheme is listed in Table 1. Using direct output encoding, each land-cover change is represented by one output node. Therefore, there are 16 output nodes in the proposed system.

Development of Training Data and Test Data

Training data selection is a problem common to all supervised training algorithms. Not only must the training data be representative of the classes, but there must also be as much separability as possible between classes in the feature space. In this study, the training sites were extracted manually from individual dates with the help of aerial photography and the standard false-color composite image (for TM data, band 4, 3, and 2 as R, G, and B in the display monitor). A set of homogeneous training regions which were representative of the classes in the study were defined and digitized on a 24-bit color screen using magnification. Multiple training sites were digitized on the screen for each class in both T_b and T_{b+1}. Then, 200 samples were randomly chosen from the training data for each class per date. The change detection in this study focuses only on the four-class scheme described above, but these samples include pixels extracted from all sub-classes to accommodate further classifications. For example, samples of ABU include agriculture land, bare soil, and urban area.

In supervised classification, spectral signatures can be characterized by their statistical representativeness (*e.g.*, mean and co-variance matrix) and spectral separability in feature space. Signatures of the same class or change class with these characteristics are assumed to be transportable over the whole image if the data are acquired under the same imaging conditions in an area with flat topography. Furthermore, in neural-network-based change detection, there is no need to use the predefined distributions of data to estimate the transitional probabilities of changes from the training data. Therefore, the condition of ground-correspondence for the training data of each change combination can be relaxed to different ground locations in each image. This general principle, that one can relax the requirement for the training pixels to be from the same ground locations, also applies to a statistical approach, such as the classifier using maximum likelihood, when the transitional probabilities of changes could be set to equal. It must be noted that this spatially non-coincident method for training might need further investigations for hilly areas because of the difference in topography or data acquired under different imaging conditions.

Based on the discussion above, a signature for class A in the T_b image and a signature for class B in the T_{b+1} image can be combined and used as the signature of the change class (A to B, denoted as A - B) in change detection. For example, one area for forest in one date and another for urban in another date can be used to train the network for the transition "forest to urban." The process of compiling the signature inputs for neural-network-based change detection is shown in Table 1. Thus, samples of input-output pairs were produced for training and testing the neural networks. These samples were further divided into two groups: samples for network training and samples for testing the trained network. The training and test data were presented to the neural network in the form of vectors derived from spectral signatures, with one value per input band and one per output change class. In this situation, inputs are represented by 12-band pixel values, and output values determine the land-cover change classes of the input pixels.

Results of Change Detection

Network Training

For the training stage of supervised change detection, the network weights are adjusted during the backpropagation training procedure. The input data vector is the pattern to be learned and the output vector is the desired set of output values to be produced by the network after training. The overall objective of training is to minimize the overall error between the desired and actual outputs of the network. The initial learning rate was set to 0.001, with adaptation occurring at every epoch in batch training. The rate of learning rate increase was set to 1.07 and the rate of learning rate decrease to 0.7. The momentum was set to 0.00005. The numbers of hidden nodes were determined by iterative trails. We started from a 12-36-36-16 configuration and concluded that a configuration of 12-36-48-16 achieved the best results in terms of the sum square error and the generalization capability of the trained network.

Network Generalization

In this work, we used direct output encoding, i.e., each output change class corresponded to one output node. The class membership of an input pixel was determined by choosing the output unit with the highest activation. This method did not use any threshold and assured that every pixel in the image was classified. The change-detection accuracy of the trained network was 100 percent on the training data. Applying the trained network to the test samples yielded a change-detection accuracy of 98.9 percent. The trained change-detection network was then used as a feed-forward network to detect changes in the entire image. It shows that the trained neural network has enough generalization capability to extend what it has learned about the training patterns to the rest of the image. The evaluation of the change-detection results is addressed in the following sub-sections.

Accuracy Assessment

We estimated the accuracy from a subset of the samples for which ground truth was available. For unbiased estimation, the number of samples for each class is roughly proportional to the histogram of the classified image. Sparsely populated change classes were discarded in the change-detection accuracy assessment due to the difficulty of finding ground truth data. For example, the change classes of Forest to Water, Agriculture/Bare/Urban to Water, and Water to Agriculture/Bare/Urban have only 44, 38, and 42 pixels, respectively, out of the

TABLE 1. OUTPUT CODING SCHEME AND SIGNATURE COMPOSITION FOR NEURAL NETWORK CHANGE DETECTION. EACH CHANGE CLASS IS REPRESENTED BY ONE OUTPUT NODE. A SIGNATURE FOR CLASS *A* IN T_b IMAGE AND A SIGNATURE FOR CLASS *B* IN T_{b+1} IMAGE ARE COMBINED AND USED AS THE SIGNATURE FOR THE CHANGE CLASS, *A* TO *B*.

Output Coding (OC) and Signature Composition (SC)		"to" Classes and Signatures Extracted in 1994							
		Forest		ABU		CWM		Water	
		OC	SC	OC	SC	OC	SC	OC	SC
"from" Classes and Signatures Extracted in 1988	Forest	1	Forest-Forest	2	Forest-ABU	3	Forest-CWM	4	Forest-Water
	ABU	5	ABU-Forest	6	ABU-ABU	7	ABU-CWM	8	ABU-Water
	CWM	9	CWM-Forest	10	CWM-ABU	11	CWM-CWM	12	CWM-Water
	Water	13	Water-Forest	14	Water-ABU	15	Water-CWM	16	Water-Water

TABLE 2. ERROR MATRIX OF THE NEURAL-NETWORK-BASED CHANGE DETECTION, CONSTRUCTED BY COMPARING THE CLASSIFICATION MAP PROVIDED BY THE NEURAL NETWORK ALGORITHM WITH THE CORRESPONDING GROUND TRUTH DATA ON 1:24,000-SCALE AERIAL PHOTOGRAPHY.

		Change Detection Results from the Proposed Neural-Network-Based Algorithm																Total
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
Ground Truth	1	199	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	200
	2	1	22	2	0	0	0	0	0	0	0	0	0	0	0	0	0	25
	3	0	1	48	1	0	0	0	0	0	0	0	0	0	0	0	0	50
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5	0	0	0	0	20	0	0	0	3	0	0	0	0	0	0	0	23
	6	0	0	0	0	0	191	4	0	0	5	0	0	0	0	0	0	200
	7	0	0	0	0	0	2	61	2	0	1	4	0	0	0	0	0	70
	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0	96	0	0	0	4	0	0	0	100
	10	0	0	0	0	0	0	0	0	1	61	7	0	0	0	1	0	70
	11	0	0	0	0	0	0	0	0	0	0	191	1	0	0	8	0	200
	12	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	1	15
	13	0	0	0	0	0	0	0	0	1	0	0	0	9	0	0	0	10
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	1	20
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	200	200
Total		200	23	50	1	20	193	65	0	102	69	202	15	13	0	28	202	1183
		Overall Accuracy: 95.6%																

512- by 512-pixel study area. These changes might be caused by different water levels and/or misregistration. The final error matrix, as shown in Table 2, was constructed by comparing the classification map provided by the neural network algorithm with the corresponding ground truth data from 1:24,000-scale aerial photography, acquired in Winter 1988 and Winter 1994, respectively. In this matrix, we put the true land-cover changes (as determined from the ground truth) on the rows and the land-cover changes detected by our algorithm on the columns. The terms on the diagonal of this matrix give correctly recognized land-cover changes, while the other terms identify errors. The overall accuracy of change detection was estimated to be 95.6 percent.

Comparison with Post-Classification Protocol

The technique of Post-Classification Comparison has been used as a benchmark method in the literature to do comparisons with other methods (Bruzzone and Serpico, 1997). The maximum-likelihood supervised classification was used to independently classify the two images using the same training sets as developed for the neural-network-based change detection. The error matrix resulted from the post-classification comparison method is shown in Table 3. By comparing the classification maps from the two dates with the ground truth data, the overall accuracy achieved was determined to be 86.5 percent. Therefore, the neural-network-based change-detection algorithm outperformed the maximum-likelihood-based Post-Classification Comparison in terms of the overall change-detection accuracy. In fact, a decrease in accuracy was present in almost all change classes.

Conclusions and Recommendations

The research reported in this paper developed and implemented the methodologies and algorithms for a change information extraction system using multitemporal remotely sensed imagery, focusing on land-cover change detection using artificial neural networks. Based on the experiments, the neural network model for digital change detection using the generalized delta rule showed a great potential as an efficient change-detection technique. Our approach to land-cover change detection

TABLE 3. ERROR MATRIX OF THE CHANGE DETECTION RESULTS PRODUCED BY THE POST-CLASSIFICATION COMPARISON METHOD USING A MAXIMUM-LIKELIHOOD SUPERVISED CLASSIFICATION.

		Change Detection Results from the Post-Classification Comparison Algorithm																Total
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
Ground Truth	1	183	2	8	0	2	0	0	0	5	0	0	0	0	0	0	0	200
	2	1	20	2	0	2	0	0	0	0	0	0	0	0	0	0	0	25
	3	3	6	38	3	0	0	0	0	0	0	0	0	0	0	0	0	50
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5	2	0	0	0	17	4	0	0	0	0	0	0	0	0	0	0	23
	6	2	6	0	0	7	175	4	0	0	5	0	0	0	1	0	0	200
	7	0	0	0	0	3	5	51	6	0	0	5	0	0	0	0	0	70
	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	10	0	0	0	7	0	0	0	75	4	0	0	4	0	0	0	100
	10	0	0	4	3	0	4	0	0	0	53	6	0	0	0	0	0	70
	11	3	0	0	0	0	5	2	0	0	0	179	4	0	0	7	0	200
	12	0	0	0	0	0	0	0	2	0	0	1	10	0	0	0	2	15
	13	0	0	0	0	0	0	0	0	2	0	0	0	7	0	1	0	10
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15	0	0	0	0	0	0	0	0	0	0	0	0	1	2	15	2	20
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	200	200
Total		204	34	52	6	36	195	57	8	82	62	191	14	12	3	23	204	1183
		Overall Accuracy: 86.5%																

is unique in that artificial neural networks are systematically used for the first time to develop an automated change-detection system identifying complete categorical land-cover change information. The advantages of this method are summarized as follows:

- This method provides complete categorical land-cover changes, i.e., complete "from-to" information which is desirable in most change-detection applications;
- Knowledge of the statistical distribution of the data is not required. This is an advantage over most statistical methods requiring modeling of the data which is difficult when there is no knowledge of the distribution functions or when the data are non-Gaussian;
- This method has the potential to provide a reliable tool for effectively integrating various remotely sensed data and existing geographic data. Multisource data can be easily added into the process by adding additional input nodes;
- The neural network approach to change detection naturally uses the data of two dates simultaneously and makes use of the time dependency of the data. This method is also free from accumulative errors, unlike the Post-Classification Comparison; and
- The trained neural network for change detection can perform change detection on a pixel-by-pixel basis in real-time. Therefore, this method has implications for real-time operation in local or regional applications.

Based on this research, the following three areas were identified for future investigations: (1) elimination or relief of the negative effects of image misregistration. The accuracy of change detection critically depends on the accuracy of image registration, and subpixel misregistration could have a marked impact on the ability of a change detector to detect real changes on the ground (Dai and Khorram, 1998a); (2) false changes caused by data inconsistency. There are variations among multitemporal images, even of the same geographic area, because of such factors as different atmospheric conditions, differences in sun angle, differences in soil moisture, difference in topography, and lack of sensor calibration; and (3) mixed pixel modeling. Most currently available remotely sensed data comes from low-resolution sensors where the ground cell itself may comprise various classes at once, i.e., the mixed pixel problem. Given the facts of lengthy neural network training, the huge data volume to be processed, and the practical demand for fast or even real-time operation, it is worthwhile to explore artificial intelligence approaches to automated change detection. Research on intelligent and automated change information extraction from remotely sensed imagery will continue to increase as the data volume becomes larger, data rates become higher, and the image processing ability of machines becomes faster.

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