The Classification using the Merged Imagery from SPOT and LANDSAT

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ABSTRACT

Several commercial companies that plan to provide improved panchromatic and/or multi-spectral remote sensor data in the near future are suggesting that ' merge' datasets will be of significant value. This study evaluated the utility of one major merging process-process components analysis and its inverse. The 6 bands of 30×30m Landsat TM data and the 10×10m SPOT panchromatic data were used to create a new 10×10m merged data file. For the image classification, 6 bands that is 1st, 2nd, 3rd, 4th, 5th and 7th band may be used in conjunction with supervised classification algorithms except band 6. One of the 7 bands is Band 6 that records thermal IR energy and is rarely used because of its coarse spatial resolution (120m) except being employed in thermal mapping. Because SPOT panchromatic has high resolution, it makes 10×10m SPOT panchromatic data be used to classify for the detailed classification. SPOT as the Landsat has acquired hundreds of thousands of images in digital format that are commercially available and are used by scientists in different fields. After the merged, the classifications used supervised classification and neural network. The method of the supervised classification is what used parallelepiped and/or minimum distance and MLC (Maximum Likelihood Classification).

The back-propagation in the multi-layer perception is one of the neural networks. The used method in this paper is MLC (Maximum Likelihood Classification) of the supervised classification and the back-propagation of the neural network. Later in this research SPOT systems and images are compared with these classification. A comparative analysis of the classifications from the TM and the merged SPOT/TM datasets will be resulted in some conclusions.

As a result, the overall accuracy at the MLC of the Merging Image was 86.972% with a KHAT of 0.830 and it at the MLC of only TM was 87.242%, while a KHAT was 0.834. But the overall accuracy at the B.P of the neural networks was 87.781% with a KHAT of 0.841 and the TM was 86.253%, while a KHAT was 0.821.

1. INTRODUCTION

Classification of remote-sensing data has traditionally been performed by classical statistical methods (e.g., bayesial and K-nearest-neighor calssifiers). In recent years, the remote-sensing community has become interested in applying neural network to data classification. Though many types of neural network models could be applied to remote-sensing data classification, most of the research work deals with few of them. One of the most widely used neural models is the Back-Propagation algorithm (BP). A study by Hepner et al. (1989) concluded that neural networks (NN) could map general land-cover types (Anderson Level I) with greater accuracy than a conventional maximum-likelihood classifier when using Landsat Thematic Mapper™ data.

A.K Skidmore et al. (1997) concluded that the neural-network approach does net offer significant advantages over conventional classification schemes for mapping eucalypt forests from Landsat TM and Ancillary GIS data at the Anderson Level III forest type level. X.long et al. (1999) studied remotely sensed change detection based on artificial neural networks It is concluded that 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. The main objective of this study was to compare MLC(Maximum Likelihood Classification) of the supervised classification with the back-propagation of the neural network of the Merged Imagery from SPOT and LANDSAT.

2. Artificial Neural Networks(ANNs)

Work on artificial Neural Networks, commonly referred to as "neural networks," has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability to organize its strutural socstityents, known as neurons, so as to perform certain computations (e.g., pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today. The general methods of this Study have been used by the back-propagation of the neural network and MLC of the supervised classification. First, The Back-propagation is one of the most important historical developments in neural networks.

2.1. Back-propagation of the neural networks

A Back-propagation algorithm was implemented for a three-layer network (see Fig. 1.) consisting of an input, hidden, and output layer because most comparable studies used the back-propagation algorithm, or a derivative of the back-propagation, so its use allows a comparison with these results; and discussions with experienced colleagues revealed a consensus that the back-propagation algorithm is generally applicable and has good modeling capabilities. The back-propagation algorithm comprises a forward and a backward phase through the neural-network structure. The first phase is forward, during which the values of the output nodes are calculated based on the GIS and remotely sensed data values input to the neural network. In the second phase, the calculated output mode values are compared with the target values. The difference between the value calculated for the node and the value of the target mode is treated as the error; this error is used to modify the weights of the connections in the previous layer. This represents one epoch of the back-propagation algorithm. In an iterative process, the output node values are again calculated, and the error is then propatated backwards. The total error in the system is calculated as the root-mean-square error between the calculated value and the target value for each mode. The algorithm continues until the total error in the system decreases to a pre-specified level, or the rate of decrease in the total system error becomes asymptotic. A brief description of the back-propagation algorithm now follows.

Let us consider a three-layer network as shown in Fig.1 to illustrate the details of the back-propagation learning algorithm. The result can be easily extended to networks with any number of layers. In this Fig .1, we have m nodes in the input layer, l nodes in the hidden layer, and n nodes in the output layer; the solid lines show the forward propagation of signals, and the dashed lines show the backward propagation of errors.

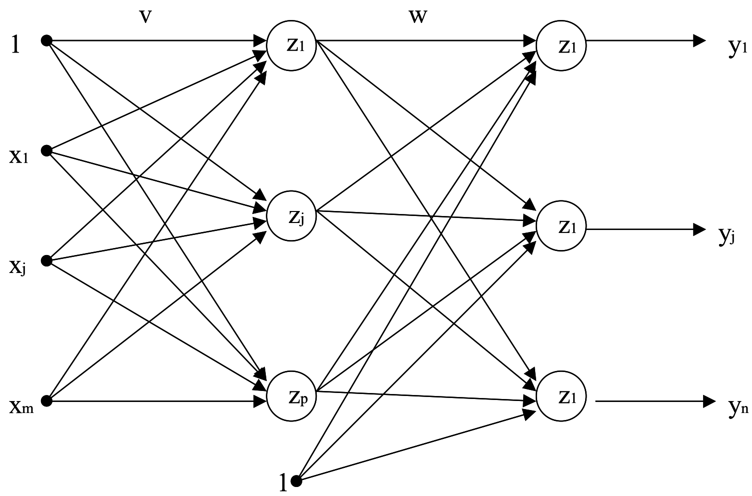

Fig 1. Three-layer back-propagation neural network.

In summary, the error back-propagation learning algorithm can be outlined in the following algorithm BP

Consider a network with Q feedforward layers, q=1,2‥‥‥,Q and let ${}^{q}net_i$ and ${}^{q}y_i$ denote the net input and output of the ith in the qth layer, respectively. The network has m input nodes and output nodes. Let ${}^{q}w_{ij}$ denote the connection weight from ${}^{q-1}y_i$ and ${}^{q}y_i$.

Input => A set of training pairs {($x^{(k)}$, $d^{(k)}$) ∣ k=1,2,‥‥‥p}, where the input vectors are augmented with the last elements as –1, that, $x^{k}_{m+1} = -1$.

Step 1 => Initialization : Choose η >0 and E_{max} (maximum tolerable error), Initialize the weights to small random values. Set E=0 and *k=1*.

Step 2 => Training loop : Apply the *k*th input pattern to the input layer (q=1): ${}^{q}y_i = {}^{1}y_i = x_i^{(k)}$ for all *i*

Step 3 => Forward propagation: Propagate the signal forward through the network using ${}^{q}y_i = a({}^{q}net_i) = a(\sum_j {}^{q}w_{ij}\,{}^{q-1}y_j)$ for each *I* and *q* until the outputs of the output layer have all been obtained.

Step 4 => Output error measure : Compute the error value and error signals ${}^{Q}\delta_i$ for the output layer:

$$E = \frac{1}{2}\sum_{i=1}^{n}(d_i^{(k)} - {}^{Q}y_i)^2 + E,$$

$${}^{Q}\delta_i = (d_i^{(k)} - {}^{Q}y_i)\,a'({}^{Q}net_i).$$

Step 5 => Error back-propagation: Propagate the errors backward to update the weights and compute the error signals ${}^{q-1}\delta_i$ for the preceding layers:

$$\Delta\,{}^{q}w_{ij} = \eta\,{}^{q}\delta_i\,{}^{q-1}y_i \qquad and \qquad {}^{q}w_{ij}^{new} = {}^{q}w_{ij}^{old} + \Delta\,{}^{q}w_{ij},$$

$${}^{q-1}\delta_i = a'({}^{q-1}net_i)\sum_j {}^{q}w_{ji}\,{}^{q}\delta_i \qquad for \qquad q = Q, Q-1, \cdots, 2.$$

Step 6 => One epoch looping : Check whether the whole set of training data has been cycled once. If k <p, then k=k+1 and go to step 1; otherwise, go to step 7.

Step 7 => Total error checking : Check whether the current total error is acceptable :If $E < E_{max}$, then terminate the training process and output the final weight; otherwise, E=0, k=1, and initiate the new training epoch by going to step 1.

End BP

3. STUDY AREA

The study area for this project is GADUC Island area in S.Korea that is lies within the Universal Transverse Mercator (UTM) Zone 52, and ranges in UTM coordinates from 180,996.00 meters west to 187,206.00 meter east and from 175065.00 meters north to 165,427.00 meters south. The TM images were from May 1997 and The SPOT image was the same as TM images. Both images were cloud free over the study area.

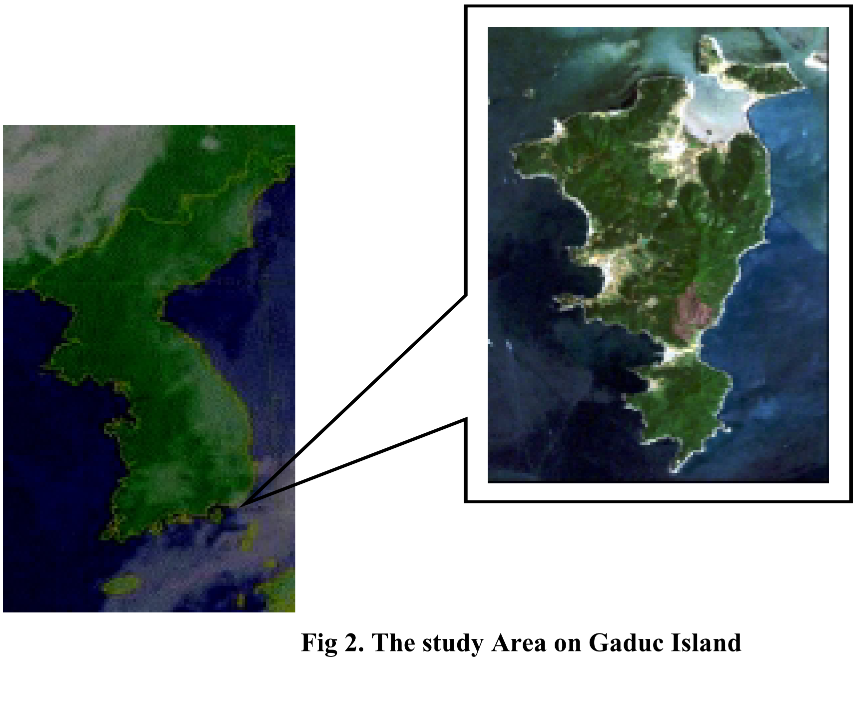

Fig 2. The study Area on Gaduc Island

4. THE MERGED METHODS

There are several possible approaches to merging the data: The Intensity-Hue-Saturation (IHS) Transform Substitutes high spatial resolution imagery for the intensity component of the low spatial resolution imagery. The bravery transform uses a ratio algorithm to merge the different images. The multiplicative method is base on the theory of the image Principal Component and Inverse Principal Component Transformation. There exist some practical limits to applying resolution merge techniques. If the resolution ratio of the two input images exceed a certain limit, for example, SPOT panchromatic(10×10) and AVHRR imagery(1,100×1,100 m), it will difficult to produce a merged image of any value.

The Principal Component approach was selected as the resolution merging technique for this research because it does not have the merging image band number limits like the IHS approach and it is more mathematically rigorous than the Bravely Transform and the Multiplicatice approaches. Principal Component assumptions using the Landsat TM and SPOT panchromatic data resolution merge were as follows.

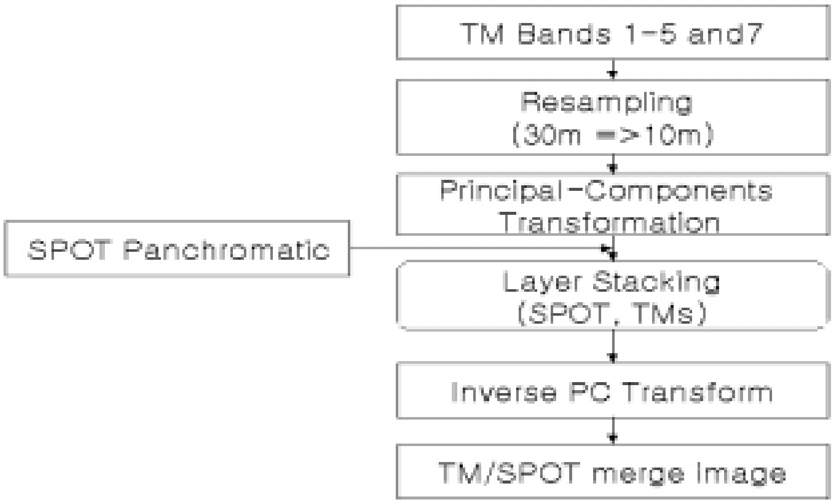

Fig. 3. The Method of Merge Process.

After Merge Process, the image classifications used both the back-propagation of the neural networks and MLC of the supervised classifications in this study.

5. RESULTS AND DISCUSSION

Authors study that area is used to demonstrate the classifying land cover which was interpreted to produce the Anderson level I Land-used map. Table1~2. Show the result of the classifications in this paper. Typically, compared with classification of the MLC in the unsupervised classification, Neural Network classification is better than MLC. Yet the result of the Neural networks classification at the Crop. Land is worse than MLC. It’s not important to get precise classification result because the aim in this paper is a classification using by the merged imagery from SPOT and LANDSAT.

Classified Data	Reference Data								
	Forest	Residential	Crop. land	Agri. Land	Rangeland	Barren Land	Water	Totals	Accuracy
Forest	151	0	1	0	0	4	0	156	96.00%
Residential	0	104	7	2	0	3	0	116	89.66%
Crop. land	0	2	51	6	0	15	1	75	68.00%
Agri. Land	1	1	31	45	3	5	0	86	52.33%
Rangeland	0	0	10	2	17	2	0	31	54.84%
Barren Land	0	12	12	3	1	175	7	210	83.33%
Water	0	0	0	0	0	5	434	439	98.86%
Totals	152	119	112	58	21	209	442	1113	
Accuracy	99.34%	87.40%	45.54%	77.59%	80.95%	83.73%	98.19%		87.78%

Table 1. The classification result of the neural networks

Classified Data	Reference Data								
	Forest	Residential	Crop. land	Agri. Land	Rangeland	Barren Land	Water	Totals	Accuracy
Forest	141	0	0	0	0	2	0	143	98.60%
Residential	0	98	5	5	1	7	0	116	84.48%
Crop. land	1	2	61	7	3	10	0	84	72.62%
Agri. Land	2	6	26	44	3	3	0	84	52.38%
Rangeland	0	0	1	1	13	0	0	15	86.67%
Barren Land	8	13	19	1	1	185	16	243	76.13%
Water	0	0	0	0	0	2	426	428	99.53%
Totals	152	119	112	58	21	209	442	1113	
Accuracy	92.76%	82.35%	54.46%	75.86%	61.91%	88.52%	96.38%		86.97%

Table 2. The classification result of MLC

Evaluations of the classifications were performed on an individual and a comparative basis within each classification set. The individual accuracy assessments were reported using classification error matrices. From these matrices, user's and producer's accuracy were calculated for all individual classes as well as overall classification accuracy. The Kappa statistic (KHAT) and its variance were calculated for overall accuracy and for each category. In the Fig.4～5, there are much noises at the merging image of TM/SPOT than only TM using the MLC of Supervised classifications, but at the BP of Neural Networks noises has reduced the merging image than only TM. At the MLC the merging image reduces overall accuracy than only TM image.

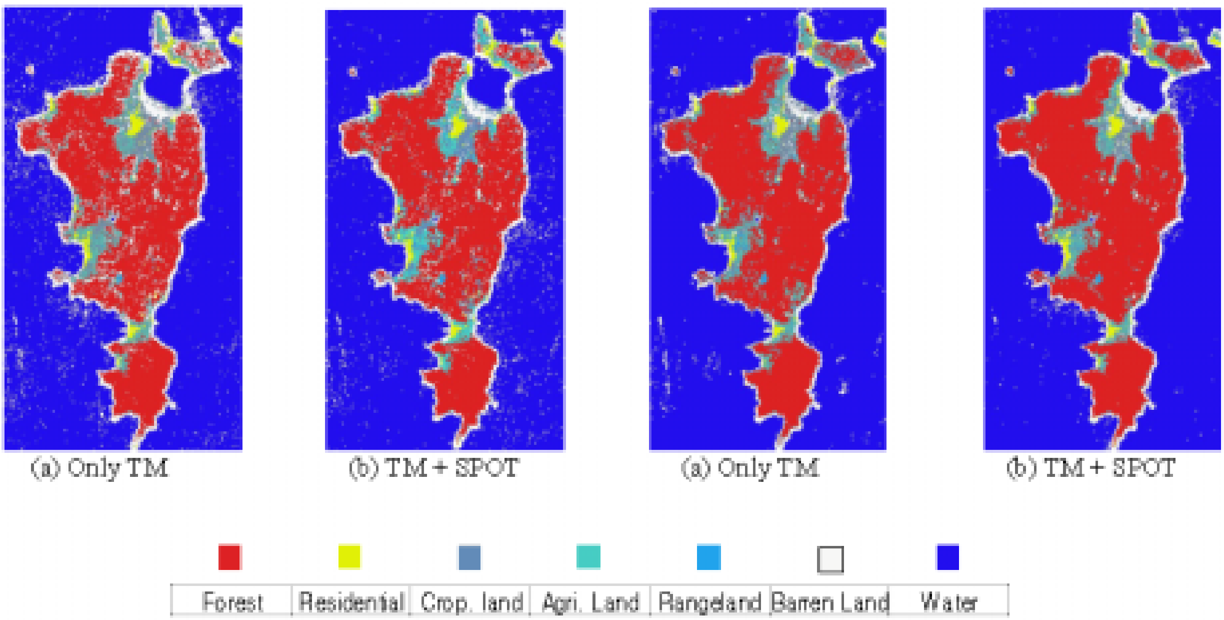

Fig 4. MLC of Supervised classifications **Fig 5. B.P of Neural Networks classifications**

Classification	IMAGE	Overall Accuracy	KHAT(%)	95% CL Low	95% CL High
MLC	TM + SPOT	86.972%	0.830	84.950%	88.995%
	Only TM	87.242%	0.834	85.237%	89.247%
Neural Networks	TM + SPOT	87.781%	0.841	85.812%	89.750%
	Only TM	86.253%	0.821	84.185%	88.321%

Table 3. Classification Results

Table 3. shows that the overall accuracy at the MLC of the Merging Image was 86.972% with a KHAT of 0.830 and it at the MLC of only TM was 87.242%, while a KHAT was 0.834. But The overall accuracy at the B.P of the neural networks was 87.781% with a KHAT of 0.841 and the TM was 86.253%, while a KHAT was 0.821.

6.CONCLUSIONS

This paper showed that almost any kind of neural network, using a Standard Back-Propagation Learning algorthm for mining the Mean Square error, is able to perform better than MLC. The reason is that the neural network is able to use a larger training set than the MLC. The results of the classifications using the merged imagery from SPOT and LANDSAT are as follows. The merged imagery improves the overall accuracy in the BP of Neural Network, yet the MLC did not significantly improve classification results over the BP of Neural Network. It shows that the MLC wasn't affected by the merge imagery. The BP of Neural Network provided the merged imagery to better classification accuracy. Finally, authors will expect higher accuracy in addition to the texture, context and so on.

REFERENCES

Hepner, G.F., T.Longan, N.Ritter, and N.Bryant, 1989. Arityficial neural network classification using a minimal training set: Comparison to conventional supervised classification, Photogrammetric Engineering & Remote Sensing, 56(4):469-473.

A.k shidmore, B.J Turner, W. Brinkhof, and E. Knowles, 1997. Performancd of a Neural Network: Mapping Forests Using GIS and Remotely Sensed Data , Photogrammetric Engineering & Remote Sensing, 63(5):501-514.

John R. Jensen, 1996. Introducetory Digital Image Processing, Prentice-Hall, pp.197-231.

Christopher M.Bishop, 1995. Neural Networks for Pattern Recognition, Clarendon Press Oxford, pp 140-147.

Chin-Teng Lin and C.S. George Lee, 1995. Neural Fuzzy Systems, Prentice-Hill, pp 236-244.

Carper, W.J., T.M. Lillesand, and R.W.Kiefer, 1990. The Use of Intensity-Hue-Saturation Transformation for Merging SPOT Panchromatic and Multispectral Image Data, Photogrammetric Engineer & Remote Sensing, 56(4), 459-467.

Cary T., 1994. A World of Possibilities: Remote Sensing Data for your GIS, Geo Info Systems, September.

Ehlers, M., 1991. Multi-Sensor Image Funsion Techniques in Remote Sensing, ISPRS Journal of Photogrammetry and Remote Sensing, 46(3), pp19-30.

Floyd F. Sabins, 1997, Remote Sensing-Principles and Interpretation , W.H. freeman and Company.

Congalton, R.G. 1991, A Review of Assessing the Accuracy of Calssifications of Remotely Sensed Data, Rempte sensing of Environment, 37(1), 35-46.