The Classifications using by 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 network. 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 merged SPOT/TM datasets will be resulted in some conclusions.

Keyword : Landsat, SPOT, Neural Network, Supervised classification.

INTRODUCTION

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.

1. Back-propagation of the neural networks

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 inthe output layer; the solid lines show the forward propagation of signals, and the dashed lines show the backwardkward propagation of errors.

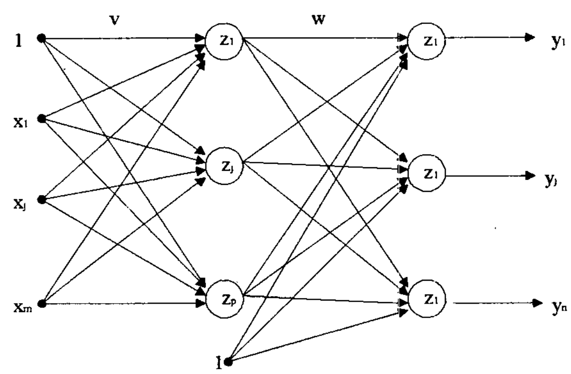


Fig 1. Three-layer back-propagation network.

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

Consider a network with Q feeforward 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 n output nodes. Let $^{q}w_{ij}$ denote the connection weight from $^{q-1}y_j$ and $^{q}y_j$.

Input: A set of training pairs $\{(x^{(k)}, d^{(k)}) \mid k=1,2,\ldots,p\}$, where the input wectors are augmented with the last elements as -1, that is, $x^{k}_{m+1} = -1$.

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

Step 2 => Training loop : Apply the kth input pattern to the input layer (q=1):

$^{q}y_i = {}^{l}y_i = x^{(k)}_i$ 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 $^{Q}y_i$ ahve all been obtained.

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

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

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

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:

$\Delta^{q}_{w_{ij}} = \eta^{q}\delta^{q-1}_{j}y_1$ and $^{q}w^{new}_{ij} = {}^{q}w^{old}_{ij} + \Delta^{q}w_{ij}$,

$^{q-1}\delta_i = a'({}^{q-1}net_i \sum_j {}^{q}w_{ij}\,{}^{q}\delta_j$ for

$q = Q, Q-1, \ldots, 2.$

step6 => One epoch looping : Clheck whether the whole set of training data has veen cycled oncd. If $k < p$, then $k = k+1$ and go to step1; otherwise, go to step 7.

step7=> 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; ptherwise, $E=0, k=1$, and initiate the new training epoch by going to step 1.

End BP

2. the maximum likelihood classification algorithm

The maximum likelihood decision rule assigns each pixel having pattern measurements or features X to the class c whose units are most probles or likely to have given rise to feature vector X. It assumes that training data statistics for each class in each band are normally distributed, that is, Gaussian. In other words, training data with bi-or trimodal histograms in a single band are not ideal. In such cases the individual modes probably represent indivisual classes that should be trained upon individually and labeled as separate classes. This would then produce unimodal, Gaussian training class statistics that would fulfill the normal distribution requirement.

Maximum likelihood classification makes use of the statistics already computed and discussed in previous sections, including the mean measurement vector M_c for each class and the covariance matrix of class c for bands k thought l, V_c, The decision rule applied to the unknown measurement vector X is

Decide X is in class c if, and only if,

$p_c \geq p_i$, where $i = 1, 2, 3 \ldots, m$ possible classes

and

p_c = { -0.5 $\log_e$ [det(Vc)] } - [0.5$(X-Mc)^t Vc^{-1}(X-Mc)$]

and det(Vc) is the determinant of the covariance matrix Vc, Therefore, to classify the measurement vector X of unknown pixel into a class, the maximum likelihood decision rule computers the value pc for each class. Then it assigns the pixel to the class that has the largest (or maximum) value.

Now let us consider the computations required. In the first pass, p1 is computed, with V1 and M1 being the covariance matrix and mean vectors for class 1. Next, P_2 is computed using V_2 and M_2. This continues for all m classes. The pixel or measurement vector X is assigned to the class that produces the largest or maximum p_c, The measurement vevtor X used in each step of the calculation consists of n elements (the number of bands being analysed) For example if all six bands were being analyzed, each unknown pixel would have a measurement vector X of

$$X = \begin{bmatrix} BV_{i,j,1} \\ BV_{i,j,2} \\ BV_{i,j,3} \\ BV_{i,j,4} \\ BV_{i,j,5} \\ BV_{i,j,6} \end{bmatrix}$$

Equation 8-22 assumes that each class has an equal probability of occurring in the terrain. Common sense reminds us that in most remote sensing applications there is a high probability of encountering some classes more often than others. Thus, we would expect more pixels to be classified as water simply because it is more prevalent in the terrain. It is possible to include this valuable a priori (prior knowledge) information in the classification decision. We can do this by weighting each class c by its appropriate a priori probability ac The equation then becomes

Decide X is in class c , if and only if,

$p_c(a_c) = P_i(a_i)$

where

$I = 1, 2, 3, \ldots, m$ possible classes
and

$p_c(a_c)$ = $\log_e$ (a_c) - { 0.5 $\log_e$ [det (V_c)]} - [0.5 $(X-M_c)^t$ $(V_c^{-1})(X-M_c)$]

This Bayes's decision rule is identical to the maximum likelihood decision tule except that it does net assume that each class has equal probabilities. A priori probabilities have been used successfully as a way of incorporating the effects if relief and other terrain characteristics in improving classification accuracy. Haralick and Fu provide an in-depth discussion of the probities decision rules. The maximum likelihood and Bayes's classification require many more computation per pixel than either the parallelepiped or minimum-distance classification algorithms. They do not always produce superior results.

The maximum likelihood classification of remotely sensed data involves considerable computation effort because it calculates a large amount of information on the class membership characteristics of each pixel. Unfortunately little of this information is made available in the conventional outship per pixel. Foody et al. (1992) suggest that more of the information generated in the classification can be output, can be computed. For example, the a posteriori probability of a pixel X belonging to class c is

$$L(C|x) = \frac{A_C p(x|C)}{\sum_{r=1}^{m} a_r P(X|r)} \qquad (8\text{-}26)$$

where p(X|c) is the probability density function for a pixel X as a member of class c,ac, is the a priori probabilities sum to 1.0 for each pixel. The a postdence should be place on the classification of each pixel. For example the analyst may decide to only keep pixel that had an a posteriori probability > 0.85. Additional fieldwork and perhaps retraining may be required for those pixels or regions in the image that do not meet these criteria. Foody e of maximum likelihood classification algorithm using probabilistic measure of class membership.

Study Area

The study area for tihs project is GADUC Island area in Pusan 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.

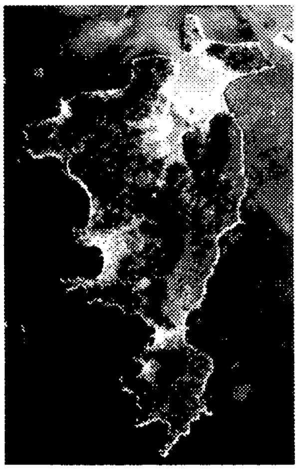


Fig 2. The study Area on Gaduc Island

The TM images were from May, 1997 and The SPOT inage was the same as TM images. Both images were cloud free over the study area.

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 Brovery 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 difficul t to produce a merged image of any value.

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

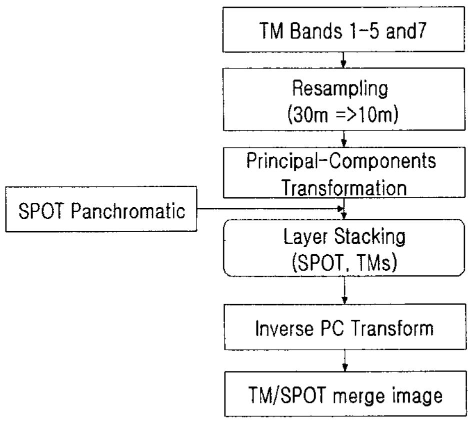
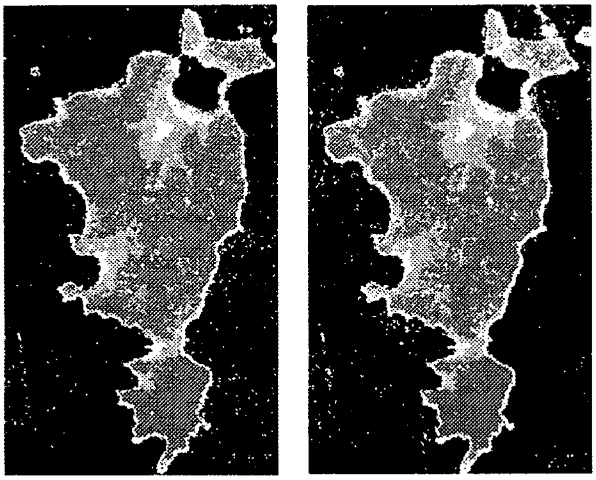


Fig 3. The Method of Merge Process.

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

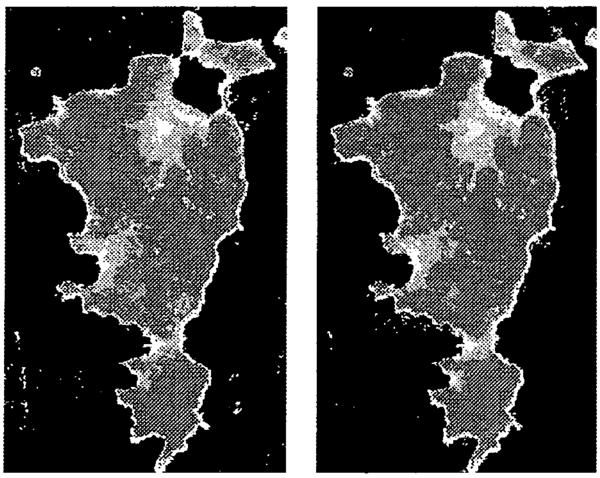
Results and Discussion

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 wuell as overall classification accuracy. The Kappa statistic(KHAT) and its variance were calculated for overall accuracy and for each category.



(a) Only TM (b) TM + SPOT

Fig 4. MLC of Supervised classifications



(a) Only TM (b) TM + SPOT

Fig 5. B.P of Neural Networks

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.

Table 1 Classification Results

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 Network	TM + SPOT	87.781%	0.841	85.812%	89.750%
	Only TM	86.253%	0.821	84.185%	88.321%

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.

CONCLUSIONS

The results of the Classifications by 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 calssification 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.

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