MULTISPECTRAL IMAGE CLASSIFICATION USING BACK-PROPAGATION NEURAL NETWORK IN PCA DOMAIN

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ABSTRACT

Recently, in classification of multispectral remote resensing image by using back-propagation neural network (BPNN), all bands of image must be used for training and classing. Disadvantage of the mentioned method not only requires more time for training and classing but also more complexity. In this paper, to decrease the mentioned disadvantage, principal component analysis (PCA) is applied to reduce dimensionality of multispectral remote sensing image as preprocessing. The first three principal components which contain information more than that of original images of 95 percents are then used for training and classing. Landsat 7 satellite TM image in visible bands of 6 is implemented to test results. We compare results of the classified multispectral remote sensing image as the proposed method with those of one as maximum likelihood classifier with principal component analysis (MLC-PCA) in term of accuracy percentage. Our results show that classification using the three-layer back-propagation neural network with principal component analysis (BPNN-PCA) is better than MLC-PCA and also it is lower complexity certainly.

1. INTRODUCTION

Having a munber of researchers has been reported to apply and verify BPNN for classing the multispectral remote sensing image [3], [4], [5], [6], [7] and [8]. Their reports have been used input data in spatial domain to input layer of BPNN. The more the number of input data bands, the more the number of nodes in input layer are. As mentioned reasons, then the processing of training and classing of classifier not only consumes more time but also increases complexity. One way to reduce time for training and classing together with complexity is that dimensionality of the number of data bands in spatial domain must be reduced by applying PCA algorithm [1] and [2] which is transforming image from spatial domain into PCA domain. Reducing dimensionality is only selecting the first three principal component images as input of BPNN-PCA. To main the highest clustering property of BPNN-PCA, we select input coding scheme as normalization coding [3] to increase accuracy percentage which is used to evaluate results comparing MLC-PCA. This paper is organized as follows. In Section 2 PCA is described; in Section 3 MLC-PCA [5] and BPNN-PCA for training and classing are described. The experimental results and conclusion are given in Section 4 and 5, respectively.

2. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) [1], [2] is an established statistical method for reducing the dimensionality of data. It is linear transformation to transform the original data onto the new data called that *principal component*. Each component contains a different variance of data and it is also uncorrelated. Normally, the first component contains the most variance. One contains the highest information content corresponding with the highest contrast. The first three principal components are employed as input of BPNN-PCA. Total variance of them is more than 95 %. By the mentioned method, ones contain more information detail than that of the three bands of original image.

The procedure of PCA method carries out as the following steps:

1) Calculate the mean vector $\mathbf{m}$ of a pixel vector $\mathbf{x}_i$, $i = 1, 2, ..., N$ as

$$\mathbf{m} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x}_i \, .$$

2) Calculate the covariance matrix $\sum$ defined generally by

$$\sum = E\{(\mathbf{X}-\mathbf{m})(\mathbf{X}-\mathbf{m})^T\}$$

where $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N\}$ is a pixel matrix, E is the expectation operator and superscript T denotes the transpose.

The covariance matrix is given by

$$\sum = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{x}_i-\mathbf{m})(\mathbf{x}_i-\mathbf{m})^T \, .$$

3) Calculate the eigenvalues $\boldsymbol{\lambda}$ of covariance matrix by solving the characteristic equation

$$\sum - \boldsymbol{\lambda}\mathbf{I} = \mathbf{0} \, .$$

where $\mathbf{I}$ is the $(N \times N)$-size identity matrix.

4) Sort the eigenvalues having the general form as following

$$\boldsymbol{\lambda} = \begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & 0 \\ 0 & 0 & \lambda_3 & \cdots & 0 \\ \vdots & & & & \\ 0 & 0 & 0 & \cdots & \lambda_N \end{bmatrix}$$

where $\lambda_1 > \lambda_2 > \ldots > \lambda_N$. The number of eigenvalues is the same as the number of input data bands. The first eigenvalue λ_1 contains the most variance—the highest contrast. The other eigenvalues are usually much smaller.

5) Generate each principal component of PCA images by projecting each pixel of original image onto the eigenvectors denoted by

$$\mathbf{Y} = \mathbf{y}_i = \sum_{j=1}^{N} a_{ij}\mathbf{x}_j = a_{i1}\mathbf{x}_1 + a_{i2}\mathbf{x}_2 + \cdots + a_{iN}\mathbf{x}_N .$$

where a_{ij} is eigenvectors by that $i = 1, 2, ..., N$. That is, the new brightness value of each pixel in the PCA images is given by a weighted sum of the corresponding pixels in each of the spectral bands.

3. CLASSIFICATION METHODS

Image classification is automatically procedures that to categorize all pixels in an image into land cover classes. In this paper proposes two methods of supervised classification, maximum likelihood and neural network classifier, to perform classify multi-spectral images.

3.1 Maximum Likelihood Classifier [5]

Maximum likelihood classifier (MLC) is a parametric classifier that relies on the second-order statistics of a Gaussian probability density function model for each class. The basic discriminant function for each class is

$$\begin{aligned} g_i(\mathbf{X}) &= p(\mathbf{X} \mid \omega_i)\, p(\omega_i) \\ &= \frac{\exp\left[-\frac{1}{2}(\mathbf{X} - U_i)^t \sum_i^{-1} (\mathbf{X} - U_i) \right] p(\omega_i)}{(2\pi)^{n/2} \left| \sum_i \right|^{1/2}} \end{aligned}$$

Where n is the number of bands for this case of 3, $\mathbf{X}$ is the input vector, U_i is the mean vector of class i for this case of 6, and $\sum_i$ is the covariance matrix of class i, that is

$$\mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad U_i = \begin{bmatrix} \mu_{i1} \\ \mu_{i2} \\ \vdots \\ \mu_{in} \end{bmatrix}$$

$$\sum_i = \begin{bmatrix} \sigma_{i11} & \sigma_{i12} & \cdots & \sigma_{i1n} \\ \sigma_{i21} & \sigma_{i22} & \cdots & \sigma_{i2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{in1} & \sigma_{in2} & \cdots & \sigma_{inn} \end{bmatrix}$$

The values in the mean vector, U_i, and the covariance matrix $\sum_i$ are estimated from the training data.

$$\mu_{ij} = \frac{1}{P_i} \sum_{l=1}^{P_i} x_{jl}, \qquad j = 1, 2, ..., n$$

and

$$\sigma_{ijk} = \frac{1}{P_i - 1} \sum_{l=1}^{P_i} (x_{jl} - \mu_{ij})(x_{kl} - \mu_{ik}),$$
$$j = 1, 2, ..., n; \qquad k = 1, 2, ..., n$$

where P_i is the number of training patterns in class i. Then discriminant function can be reduced by taking natural log and discarding the constant π term to

$$g_i(\mathbf{X}) = -\ln\left|\sum_i\right| - (\mathbf{X} - U_i)^T \sum_i^{-1} (\mathbf{X} - U_i)$$

3.2 Neural Network Classifier

One of neural network architecture which is suitable to apply for classing multispectral remote sensing image is a three-layer back-propagation network. The first layer is input layer which consists of nodes of 3 so as to correspond with input data, the first three principal component, and the output layer consists of nodes of 6 so as to correspond with a desired classes of 6—water, soil, mountain, forest, urban and building. As mentioned, the single hidden layer is then selected and here consists of nodes of 14. Activation function is sigmoid one defined as

$$f(NET) = \frac{1}{1 - e^{-NET}}$$

where NET is the sum of weighted inputs to the processing node.

In this paper, input coding scheme is normalization coding selected [3] because of maintaining the highest clustering property. The coded normalized value which is fed to input layer of network for range of 0 to 1 can be obtained as follow :

$$X_{nor} = \frac{X_f - X_{f_{\min}}}{X_{f_{\max}} - X_{f_{\min}}}$$

where $X_{f_{\min}}$ and $X_{f_{\max}}$ are the minimum and maximum values of each of principal component.

4. EXPERIMENTAL RESULTS

The data used to test all of results in this paper is the satellite imagery acquired by the Landsat 7 in Enhanced Thematic Mapper+ system in Kanjanaburee province, Thailand. Also we use particularly visible bands—1, 2, 3, 4, 5 and 7. The size of image is 8296×8871 with 8 bit resolution which is 256 gray levels. From the data, we selected a sub-region of 512×516 pixels. The selected area is shown in Fig. 1. All of the original images as mentioned in spatial domain is transformed into PCA domain by using PCA algorithm so as to reduce dimensionality. The resulted images consist of the first three component images shown in Fig. 2. The first component image (PC1) is the largest eigenvalue which mean that it contains the most information content. The other component images (PC2 and PC3) are lower. We use the first three component images as input data by which each component image is normalized and fed to input layer of neural network . Before using MLC and BPNN to classify, training procedure is first performed. All of the first three principal component image is used for training and test. Fig. 2 only shows the PC1 selected pixel areas which consists of classes of 6—water, soil, mountain, forest, urban and building. The number of selected pixels of each class is indicated in Table 1 for training and test of both MLC and BPNN. For MLC, the statistical numerical values of the first three principal component data in each class—minimum values (min), maximum values (max), mean values (mean) and standard deviation (std) is indicated in Table 2. Also Table 3 indicates covariance matrix of each class. The numerical results to test the accuracy of both MLC and BPNN are indicated in table 4 and 5, respectively. From such results, see that BPNN-PCA shows higher accuracy enough when comparing with MLC-PCA and Table 6 indicates comparing accuracy percentage as classifier for training and test by BPNN-PCA and MLC-PCA. Which see that BPNN-PCA is better than MLC-PCA in term of accuracy percentage. To visually show results, the satellite image of 512×512 pixels is implemented to classify as the mentioned classes. Fig 4 and 5 show the classified images by MLC-PCA and BPNN-PCA, respectively.

5. CONCLUSION

In this paper, we propose the one way to implement BPNN-PCA instead of BPNN so as to reduce complexity and time —which not include time for calculating PCA for training and classing everthough the accuracy of BPNN is more slight than that of BPNN-PCA but time used for BPNN-PCA training is reduced of half. We compare the results of BPNN-PCA with MLC-PCA seeing that our method is better in term of accuracy percentage of both training and test but not taking into account of time of MLC-PCA which is less than BPNN-PCA.

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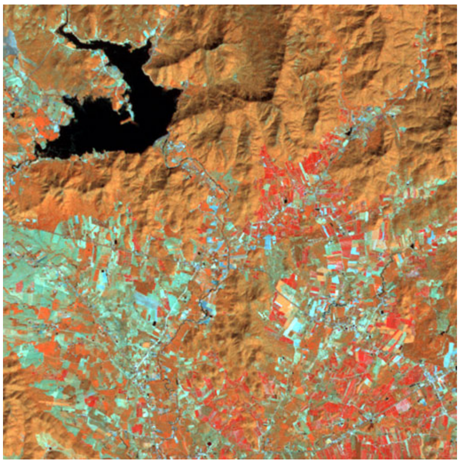
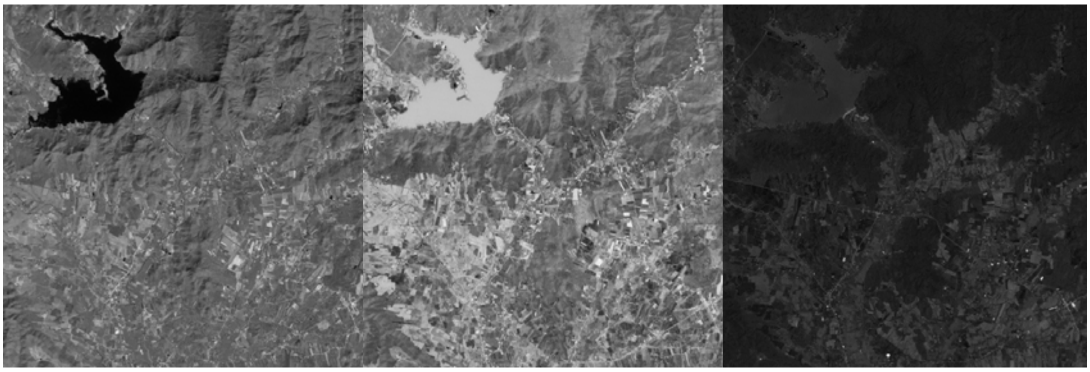
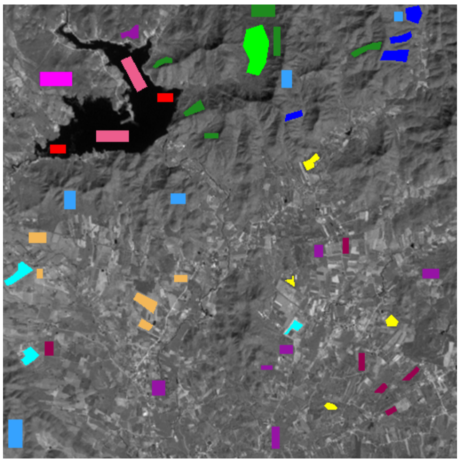


Fig. 1 The RGB image from Band 4, 5 and 7.



Principal component 1 Principal component 2 Principal component 3

Fig. 2 The first three principal component images, PC1, 2 and 3.



training	Test	Classes
		Water
		Soil
		Forest
		Mountain
		Urban
		Building

Fig. 3 The selected pixel areas of the PC1 image used for training and test.

Table 1 The number of pixels in each class used for training and test.

Number of pixels	**Classes**						
	Water	Soil	Forest	Mountain	Urban	Building	Total
Training	360	1,199	964	576	696	439	4,234
Test	991	1,324	1,339	1,583	870	717	6,824
Total	1,351	2,523	2,303	2,159	1,566	1,156	11,058

Table 2 The statistical numerical values in each class of PC1, 2 and 3 used for trainging and test.

Components	Classes	Min.	Max.	Mean	Std.
#1	Water	5	31	10.43	4.71
	Soil	52	101	71.62	7.79
	Forest	82	129	107.80	7.48
	Mountain	72	108	90.48	4.96
	Urban	112	217	142.16	26.92
	Building	67	144	86.93	7.35
#2	Water	187	199	196.05	1.76
	Soil	102	143	126.37	6.78
	Forest	68	115	89.61	7.16
	Mountain	85	147	116.10	10.72
	Urban	150	255	186.86	18.26
	Building	42	98	69.57	10.15
#3	Water	40	60	49.73	3.19
	Soil	13	39	29.40	2.84
	Forest	18	35	26.86	2.50
	Mountain	21	54	31.84	3.61
	Urban	14	66	31.66	9.51
	Building	30	86	68.74	6.45

Table 3 Covariance matrix in each class of PC1,2 and 3.

Water				Soil				Forest			
#	1	2	3	#	1	2	3	#	1	2	3
1	22.1508	-0.5937	-1.4761	**1**	60.6636	-26.8171	-9.7219	**1**	56.8972	-44.0337	-3.3597
2	-0.5937	3.1031	0.9835	**2**	-26.8171	46.9186	-0.4575	**2**	-44.0337	51.2235	-1.1388
3	-1.4761	0.9835	10.1682	**3**	-9.7219	-0.4575	8.0428	**3**	-3.3597	-1.1388	6.2380
Mountain				**Urban**				**Building**			
#	1	2	3	#	1	2	3	#	1	2	3
1	24.6325	-4.2949	3.0013	**1**	724.7625	338.6531	196.7961	**1**	53.9653	14.3213	-13.4774
2	-4.2949	116.0187	-6.3538	**2**	338.6531	333.2662	113.4497	**2**	14.3213	102.9669	-23.2038
3	3.0013	-6.3538	13.0562	**3**	196.7961	113.4497	90.3692	**3**	-13.4774	-23.2038	29.7052

denote order of principal components

Table 4 Results of classification in the selected testing area by MLC-PCA.

Classes	Results						
	Water	Soil	Forest	Mountain	Urban	Building	Total
Water	991	0	0	0	0	0	991
Soil	0	1,305	1	2	0	0	1,308
Forest	0	0	1,193	15	0	0	1,208
Mountain	0	2	127	1,237	0	2	1,368
Urban	0	17	17	19	871	0	924
Building	0	0	1	310	0	715	1,026
Total	991	1,324	1,339	1,583	871	717	6,825
Accuracy (%)	100	98.56	89.10	78.14	100	99.72	92.48

Table 5 Results of classification in the selected testing area by BPNN-PCA.

Classes	Results						
	Water	Soil	Forest	Mountain	Urban	Building	Total
Water	991	2	0	0	0	0	993
Soil	0	1,322	6	7	0	0	1,335
Forest	0	0	1,305	40	0	1	1,346
Mountain	0	0	24	1,490	2	35	1,551
Urban	0	0	4	1	869	0	874
Building	0	0	0	45	0	681	726
Total	991	1,324	1,339	1,583	871	717	6,825
Accuracy (%)	100.00	99.85	97.46	94.13	99.77	94.98	97.55

Table 6 Comparing accuracy percentage for classification by BPNN-PCA and MLC-PCA.

Classifier	Component No.	Used Area	Accuracy
Maximum likelihood	1, 2 and 3	Training	95.91 %
		Test	92.48 %
Neural network	1, 2 and 3	Training	96.62 %
		Test	97.55 %

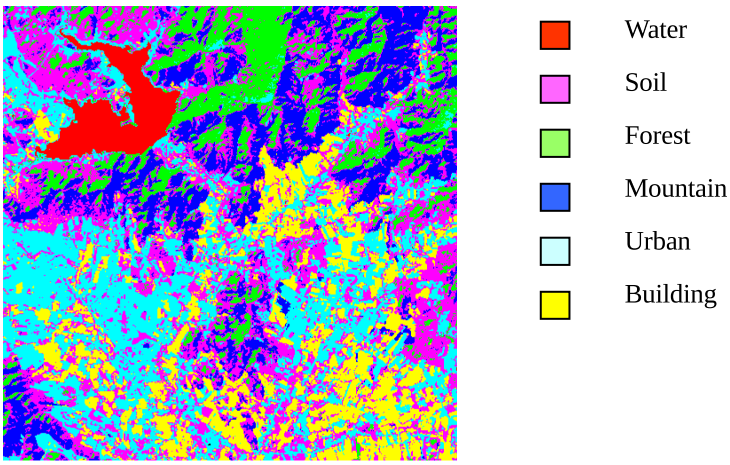


Fig. 4 The classified image by MLC-PCA.

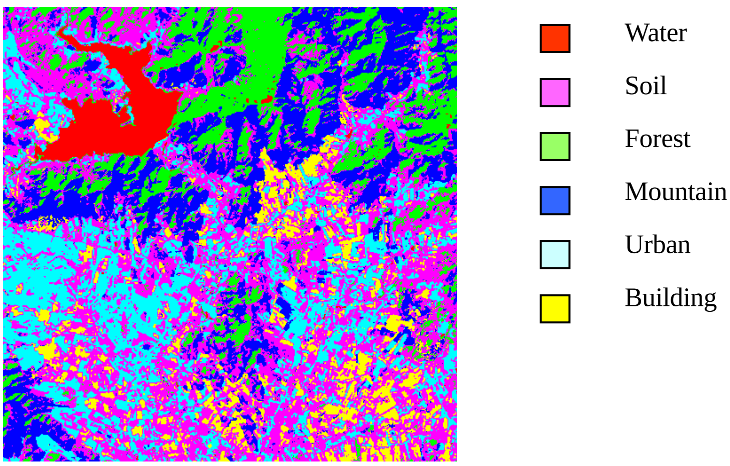


Fig. 5 The classified image by BPNN-PCA.