ISSN-1411-1284

Performance Comparison Study of Explicit Fuzzy and Gaussian Maximum Likelihood Methods for Multi-Band Landsat TM Image Classification

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Abstract - This paper evaluates the classification accuracy and complexity of Explicit Fuzzy (EF) and Gaussian Maximum Likelihood (GML) methods for multi-band Land Satellite (Landsat) Thematic Mapper (TM). Fuzzy approach has been expected to be more capable to solve uncertainties compared to the conventional statistical approach. The EF method consists of the following three steps. Each corresponding pixels of multi-band Landsat TM images are transformed into a matrix of membership degrees that forms a representation of fuzzy input values. A minimum fuzzy reasoning rule is applied to the fuzzy input values to get a fuzzy output value of each corresponding multi-band pixels. The last step is the defuzzification process based on the maximum degree of membership. In the case study of using small number of bands (two bands) both the EF and GML methods give a comparable good classification accuracy and complexity. But when the number of bands increases to seven bands, the running time of EF increases to twice or three times longer than the GML, while their classification accuracies remain about the same to the ones using only two bands.

I. Introduction

This study was carried out due to the claim that the use of Explicit Fuzzy (EF) method gives better classification accuracy and about the same complexity compared to the use of conventional Gaussian Maximum Likelihood (GML) method [1]. According to the theory [2], the fuzzy approach usually has more complexity compared to the statistical due to the computation of the membership function.

The GML is a hard classification method which may be not good for mixed-pixel area. The EF is a fuzzy classification method that is expected to perform better in solving uncertain problems. Due to the claim made by Melgani [1] that the running time of EF is about the same to the GML, it will be interested to have the EF method with the expectation that it may give better classification accuracy. Another interesting thing is that the EF method have used a Gaussian model to compute the membership function.

II. Data and Methodology

Three sets of seven-band Land Satellite (Landsat) Thematic Mapper (TM) data were used for experiments. The areas include Middle Java, Saguling, and Riau. The EF [1] and GML methods were implemented using MATLAB facility for comparison purpose.

The training and testing processes have been done using configuration of 25% samples for training and 75% samples for testing and configurations of 50%-50% and 75%-25%, respectively. These three configurations of sample data for training and testing are meant to see the influence of training sample data size. User accuracy and producer accuracy are used as classification accuracy measures and generalization measures. Running time measures are used as complexity measures of the EF and GML methods.

ISSN-1411-1284

III. The Explicit Fuzzy (EF) Method

Hard or crisp classification uses a principal of 'one pixel belongs to only one object class', while fuzzy classification assumes that 'one pixel may belong to several classes of objects'. EF method consists of three steps: (i) explicit fuzzification; (ii) minimum fuzzy reasoning rule; and (iii) defuzzification [1].

III.1. Explicit Fuzzification

Explicit fuzzification estimates each band contribution to each class of object and is represented using a Gaussian model. Fuzzy domain consists of several fuzzy sets that represent a band. Each fuzzy set consists of several fuzzy subsets that represent an object class. Each fuzzy subset of class j in fuzzy set band n, where $n = 1, 2, 3, \ldots, N$, is defined by a membership function $f_{n,j}(x_n)$, x_n is the gray level intensity of pixel $\underline{X}$ in band n. The representation of pixel $\underline{X}$ in N-dimensional is as follows:

$$\underline{X} = [x_1, x_2, \ldots, x_n, \ldots, x_N]^T, \qquad (1)$$

where N is the number of bands. Gaussian is chosen to be a model of the membership function due to its robustness and simplicity.

The mean and standard deviation of each class intensity distribution within each band are used to compute the membership function of each pixel. The mean (μ) of each class signature represents the ideal pixel of the corresponding class that does clearly belong to a certain class of object. The standard deviation (τ) of each class signature represents the range of its fuzzy subset. The membership function of class j in band n can be represented as follows:

$$f_{n,j}(x_n) = \exp\left(-\frac{(x_n - \mu_{n,j})^2}{2\tau_{n,j}^2}\right), \qquad (2)$$

where $\mu_{n,j}$ is the mean of class j in band n, and $\tau_{n,j}$ is the standard deviation of class j in band n, $j = 1, 2, 3, \ldots, J$; $n = 1, 2, 3, \ldots, N$. J is the number of object classes and N is the number of bands.

Fuzzification process computes the degree of membership of each pixel for all class j and band n. As a result an input fuzzy matrix *Fip* with an order of *NxJ* is obtained. For a multi-band images that have J number of object classes and N number of bands, the input fuzzy matrix *Fip* can be represented as follows:

$$\underline{Fip} = \begin{bmatrix} f_{1,1}(x_1) & f_{1,2}(x_1) & \ldots & f_{1,J}(x_1) \\ f_{2,1}(x_2) & f_{2,2}(x_2) & \ldots & f_{2,J}(x_2) \\ \ldots & \ldots & \ldots & \ldots \\ f_{N,1}(x_N) & f_{N,2}(x_N) & \ldots & f_{N,J}(x_N) \end{bmatrix} \qquad (3)$$

III.2. Minimum Fuzzy Reasoning Rule

Minimum fuzzy reasoning rule is applied to the input fuzzy matrix *Fip*. The most effective membership function over band n that characterizes an object class j is the minimum one. Finally, an output fuzzy vector *Fop* with an order of J is obtained as shown in Equation (4).

$$\underline{F}'op = [F_1'(\underline{X}), F_2'(\underline{X}), \ldots, F_J'(\underline{X})]^T, \qquad (4)$$

$$\text{where } F_i'(\underline{X}) = \min(f_{n,i}(x_n)) \qquad (5)$$

III.3. Defuzzification

Defuzzification is done by applying a maximum rule to the obtained *Fop* to get a single hard output. The maximum value represents the most similarity measure of a pixel belongs to a certain class. A pixel belongs to class j if only if:

$$\forall i \in 1,2,\ldots,N \text{ dan } i \neq j, F_j(\underline{X}) \geq F_i(\underline{X}) \qquad (6)$$

IV. The Gaussian Maximum Likelihood (GML) Method

A pattern vector in N-dimensional space can be represented as a vector $x = (x_1, x_2, \ldots, x_N)^T$ and there are pattern classes $\omega_1, \omega_2, \ldots, \omega_J$, $j = 1,2,\ldots,J$. J is the number of pattern classes. If each pattern class is assumed to have a Gaussian distribution, then the Gaussian density function of pattern x given j^{th} pattern class [3,4], is shown in Equation (7). m_j is the mean vector of object class j and C_j is the covariance matrix of object class j. The

GML classifier will assign a pattern class x to an object class ω_j if and only if the result of Equation (8) has a maximum value for a certain j.

$$p(x/\omega_j) = \frac{1}{(2\pi)^{B/2}\left|C_j\right|^{1/2}} \exp\left(-\frac{1}{2}(x-m_j)^T C_j^{-1}(x-m_j)\right), j = 1,2,\ldots,J \tag{7}$$

$$d_j(x) = \ln P(\omega_j) - \frac{1}{2}\ln\left|C_j\right| - \frac{1}{2}\left[(x-m_j)^T C_j^{-1}(x-m_j)\right] \tag{8}$$

V. Experimental Results

The experiments have used all bands and two optimal combination of bands. Configurations of 25%-75%, 50%-50%, and 75%-25% portions of samples for training and testing are used. Producer and user accuracies were used for measuring classification accuracies. Experimental results based on Saguling data area are shown in Table 1, Table 2, and Table 3. Table 1 shows the results of using 2 and 7 bands, using different sample portions for training and testing, and their classification accuracy based on the user and producer accuracies. Table 2 shows the computation complexity based on running time, and Table 3 shows the degree of generalization based on the difference between the user and producer accuracies.

VI. Concluding Remarks

Based on the case study using data of Middle Java, Saguling, and Riau area the following conclusions can be summarized. In the case study of using small number of bands (two bands) both the EF and GML methods give a comparable good classification accuracy, complexity, and level of generalization. But when the number of bands increases to seven bands, the running time of EF increases to twice or three times longer than the GML, while their classification accuracies remain about the same to the ones using only two bands.

Table 1. Classification accuracies for Saguling case study.

Classification Accuracy			25% Training - 75% Testing		50% Training - 50% Testing		75% Training - 25% Testing	
			PA	UA	PA	UA	PA	UA
All bands are used	EF	Training	92.8	93.4	94.6	96.59	94.53	94.65
		Testing	84.4	87.79	82.6	86.3	95.6	95.71
	GML	Training	100	100	99.6	99.61	97.86	97.91
		Testing	74.06	80.54	90	91.22	99.6	99.6
2 bands of Principal Component Transform (PCT) are selected	EF	Training	90.8	90.87	94.2	94.21	92.4	92.5
		Testing	81.53	83.64	81.8	84.99	93.6	94
	GML	Training	81.2	82.72	90.2	91	94.4	94.58
		Testing	75.73	76.93	75.2	79.27	95.6	96.13
2 original bands (band 2 and 5) are selected	EF	Training	81.6	82.16	93.8	94.04	92.66	92.88
		Testing	82.93	87.23	82.4	85.39	91.6	92.54
	GML	Training	97.2	96.57	98.2	93.13	95.2	95.1
		Testing	89.73	90.08	86.8	88.67	96	97.24

ISSN-1411-1284

Tabel 2. Running time complexity for Saguling case study.

Running Time	Classifier	25% - 75%	50% - 50%	75% - 25%
All bands are used	EF	83.741	83.77	84.441
	GML	39.627	39.266	39.627
2 bands of PCT are used	EF	31.124	30.974	30.924
	GML	36.202	35.952	35.992
2 original bands are used	EF	30.934	31.074	30.885
	GML	36.142	36.132	36.082

Tabel 3. Level of generalization for Saguling case study.

$\Delta_{maks} = \|PA - UA\|$			25%, - 75%	50%, - 50%	75%, - 25%
All bands are used	EF	Training	0.6	1.99	0.12
		Testing	3.39	3.7	0.11
	GML	Training	0	0.01	0.05
		Testing	6.48	1.22	0
2 bands of PCT are used	EF	Training	0.07	0.01	0.1
		Testing	2.11	3.19	0.4
	GML	Training	1.52	0.8	0.18
		Testing	1.2	4.07	0.53
Band 2 and band 5 are used	EF	Training	0.56	0.24	0.22
		Testing	4.3	2.99	0.94
	GML	Training	0.63	5.07	0.1
		Testing	0.35	1.87	1.24

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