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Research Article

Fuzzy Logic Based RS Image Classification Using Maximum Likelihood and Mahalanobis Distance Classifiers

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Abstract

The conventional hard clustering method restricts each point of data set to exclusively just one cluster. As a consequence, with this approach the segmentation results are often very crispy, i.e., each pixel of the image belongs to exactly just one class. However, in many real situations, for images, issues such as limited spatial resolution, poor contrast, overlapping intensities, and noise and intensity in-homogeneities variation make this hard (crisp) segmentation a difficult task. The fuzzy classifier makes use of spatial features extracted from a multispectral data, and a classification image is generated using maximum likelihood classification. Fuzzy cluster analysis is performed by allowing gradual memberships, thus offering the opportunity to deal with data that belong to more than one cluster at the same time. Most fuzzy clustering algorithms are objective function based. They determine an optimal classification by minimizing an objective function. In objective function based clustering usually each cluster is represented by a cluster prototype. A case study is presented on different Fuzzy classification methods by varying the parameters and a comparison is done as to find which method gives higher accuracy and Kappa value. Two classification methods are used here. They are: Maximum Likelihood Classifier and Mahalanobis Distance Classifier. The data considered contains both vegetation and water bodies in equal proportion. The proposed approach decreases the number of misclassifications between the Sea Water and River Water classes and the number of misclassifications between the Hilly Vegetation and Plain Land Vegetation classes raising the overall accuracy to above 80%.

Keywords: *Fuzzy C-Means (FCM), Fuzzy Supervised Classification, Maximum Likelihood Classification, Mahalanobis Distance Classification.*

Introduction

Image classification is a complex process that may be affected by many factors. Effective use of multiple features of remotely sensed data and selection of suitable classification method are significant for improving classification accuracy. Non parametric classifiers such as fuzzy logic, neural network, decision tree classifier and knowledge based classifiers have increasingly become important approaches for multisource data classification. In general image classification can be grouped into supervised and unsupervised, or parametric and non-parametric, or hard and soft (fuzzy) classification, or pixel, subpixel and perfield. In this paper, a Fuzzy clustering based method for image segmentation is considered.

Clustering is a process for classifying objects or patterns in such a way that samples belonging to same group are more similar to one another than samples belonging to different regions. Many clustering strategies have been used, such as the hard clustering scheme and the fuzzy clustering scheme. The conventional hard clustering method restricts each point of data set to exclusively just one cluster. As a consequence, with this approach the segmentation results are often very crispy, i.e., each pixel of the image belongs to exactly just one class. However, in many real situations, for images, issues such as limited spatial resolution, poor contrast, overlapping intensities, and noise and intensity in-homogeneities variation make this hard (crisp) segmentation a difficult task. In the other hand, fuzzy clustering as a soft segmentation method has been widely studied and successfully applied in image segmentation.

Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods.

2. Parametric approach

There are many classifier algorithms. In this paper we

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mainly consider the following two classifier algorithms.

- Maximum Likelihood Classifier
- Mahalanobis Distance

The maximum likelihood procedure assumes that the training data statistics for each class in each band are normally distributed (Gaussian). Training data with bi- or n-modal histograms in a single band are not ideal. In such cases the individual modes probably represent unique classes that should be trained upon individually and labelled as separate training classes. This should then produce unimodal, Gaussian training class statistics that fulfil the normal distribution requirement.

The estimated probability density functions for class w_i (e.g., forest) is computed using the equation (1).

$$\hat{p}(x \mid w_i) = \frac{1}{(2\pi)^{\frac{1}{2}}\hat{\sigma}_i}\exp\left[-\frac{1}{2}\frac{(x-\hat{\mu}_i)^2}{\hat{\sigma}_i^{\,2}}\right] \quad (1)$$

where, exp [ ] is e (the base of the natural logarithms) raised to the computed power, x is one of the brightness values on the x-axis, $\hat{\mu}_i$ is the estimated mean of all the values in the training class, and $\hat{\sigma}_i^{\,2}$ is the estimated variance of all the measurements in this class. Therefore, we need to store only the mean and variance of each training class to compute the probability function associated with any of the individual brightness values in it.

If our training data consists of multiple bands of remote sensor data for the classes of interest then in that case we compute an n-dimensional multivariate normal density function using:

$$p(X \mid w_i) = \frac{1}{(2\pi)^{\frac{n}{2}}|V_i|^{\frac{1}{2}}}\exp\left[-\frac{1}{2}(X-M_i)^T V_i^{-1}(X-M_i)\right] \quad (2)$$

where, $|V_i|$ is the determinant of the covariance matrix, V_i^{-1} is the inverse of the covariance matrix, and $(X-M_i)^T$ is the transpose of the vector $(X-M_i)$. The mean vectors (M_i) and covariance matrix (V_i) for each class are estimated from the training data.

Mahalanobis distance classification is similar to minimum distance classification, except that the covariance matrix is used in the equation. Variance and covariance are figured in so that clusters that are highly varied lead to similarly varied classes, and vice versa. For example when classifying urban areas-typically a class whose pixels vary widely-correctly classified pixels may be farther from the mean than those of a class for water, which is usually not a highly varied class. The Mahalanobis distance algorithm assumes that the histograms of the bands have normal distributions.

Formally, the Mahalanobis distance of a multivariate vector $x = (x_1, x_2, x_3, ..., x_N,)^T$ from a group of values with mean $\mu = (\mu_1, \mu_2, \mu_3, ..., \mu_N,)^T$ and covariance matrix S is defined as:

$$D_M(x) = \sqrt{(x-\mu)^T S^{-1}(x-\mu)} \quad (3)$$

Mahalanobis distance (or "generalized squared interpoint distance" for its squared value) can also be defined as a dissimilarity measure between two random vectors $\vec{x}$ and $\vec{y}$ of the same distribution with the covariance matrix S :

$$\mathrm{d}(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T S^{-1}(\vec{x}-\vec{y})} \quad (4)$$

3. Supervised fuzzy classification

Due to the large numbers of spectrally similar land cover types present in the urban environment, traditional classification approaches such as maximum likelihood often result in significant numbers of misclassifications, especially between the Road and Building classes, and the Grass and Tree classes. By utilizing spatial features in addition to the spectral information, the Fuzzy pixel-based classifier is able to more accurately classify high-resolution imagery of urban areas.

However, more detail is needed to accurately represent the land cover types present in dense urban areas. A non-road, non-building Impervious Surface class is also needed to represent features such as parking lots, concrete plazas, etc. To distinguish between these urban land cover classes, an object based classification approach is used to examine features such as object shape and context (neighbourhood) and then classify the image objects using a Fuzzy logic rule base. To facilitate object classification, the imagery is first segmented with a region merging segmentation technique. Several features are extracted from the image objects and used by the object-based classifier along with the Fuzzy pixel-based classification.

4. Analysis and results

To validate the applicability of the proposed method, a case study is presented in this section, which is carried out on IRS-P6/LISS III sample image with 23.5m resolution. The area considered for analysis purpose is a rectangular area between the points 13° 96'N 74° 43'E / 13° 97'N 75°21'E as illustrated in Fig.1. Fuzzy based image classification can be carried out in different ways applying different parametric rules. In this case study, two classification methods are mainly considered as parametric rules. They are: Maximum likelihood classification and Mahalanobis distance classification.

The analysis is carried out by varying the number of classes and also by changing the number of classes per pixel. Different classification methods yields different results and none of the methods is suitable for variable classes and variable pixels. Depending upon the information needed about the classification, suitable classes and suitable classes per pixel should be selected. The selection of a particular method is dependent on number of classes and number of classes per pixel. The suitability of a particular scheme depends to some extent on the nature of the image to be classified. The performance of the methods on the training /validation data can be used to decide on the best classifier for a given situation.

Fig. 1. 23.5m resolution image used for classification study.

Table I shows the overall accuracy values for all the set of points considered on the classified image for the two classification methods used when the number of classes is 11 and number of classes per pixel is 5. Fig.2 indicates the graph of classification accuracy versus the no of points selected on the data. It can be analysed from Fig.2 that MLC produces higher accuracy value and shows less variation in accuracy value compared to the other method. Similarly, TABLE II shows the Kappa values for 11 classes and 5 classes per pixel for the two classification methods and Fig.3 illustrates its graph.

Table I Overall classification accuracy values when number of classes is 11 and number of classes per pixel is 5.

No. Of Points Selected	Maximum Likelihood Classification	Mahalanobis Distance Classification
10	90.00%	80.00%
20	85.00%	70.00%
30	83.33%	76.67%
40	82.50%	77.50%
50	82.00%	80.00%
60	85.00%	81.67%
70	82.86%	84.29%
80	82.50%	85.00%

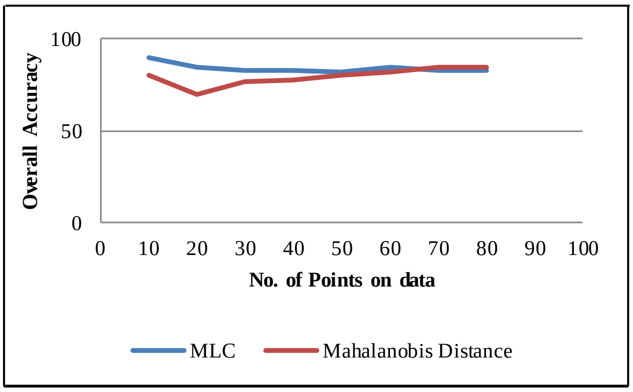

Fig. 2. Graph showing the variation of accuracy values with respect to the number of points selected on the data, for Table I.

The procedure is repeated for different number of classes and number of classes per pixel. For the dataset considered, results have been evaluated for: 11 classes and 5 classes per pixel, 11 classes and 8 classes per pixel and 11 classes for 10 classes per pixel.

Table II Overall kappa statistics when the number of classes is 12 and number of classes per pixel is 5.

No. of points selected	Maximum Likelihood Classification	Mahalanobis Distance Classification
10	0.8305	0.7143
20	0.8020	0.6091
30	0.7751	0.6624
40	0.7565	0.6648
50	0.7432	0.7081
60	0.7707	0.7218
70	0.7419	0.7523
80	0.7358	0.7651

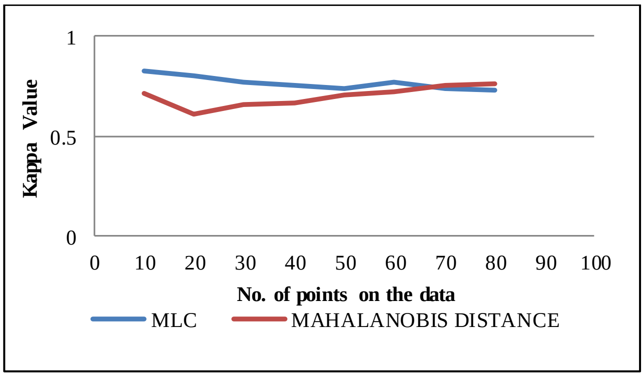

Fig. 3. Graph showing the variation of Kappa values with respect to the number of points selected on the data, for Table II.

It can be seen from TABLE I and TABLE II that, for 11 classes and 5 classes per pixel, MLC produces best classification results over the data considered.

Table III and Table IV indicate the Overall Classification Accuracy and Kappa values when the Number of Classes is 11 and Number of Classes per pixel is 8.

Table III Overall classification accuracy values when the number of classes is 11 and number of classes per pixel is 8.

No. Of Points Selected	Maximum Likelihood Classification	Mahalanobis Distance Classification
10	90.00%	90.00%
20	90.00%	85.00%
30	90.00%	83.33%
40	92.50%	82.50%
50	90.00%	86.00%
60	88.33%	85.00%
70	87.14%	81.43%
80	86.25%	80.00%

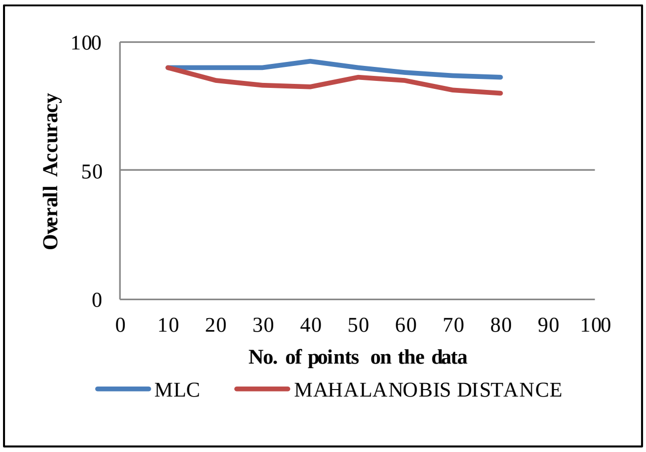

Fig. 4. Graph showing the variation of accuracy values with respect to the number of points selected on the data, for Table III.

Table IV Overall kappa statistics when the number of classes is 11 and number of classes per pixel is 8.

No. Of Points Selected	Maximum Likelihood Classification	Mahalanobis Distance Classification
10	0.7872	0.8182
20	0.7633	0.6875
30	0.8089	0.6732
40	0.8212	0.6933
50	0.7713	0.7568
60	0.7513	0.7339
70	0.7302	0.6844
80	0.7217	0.6636

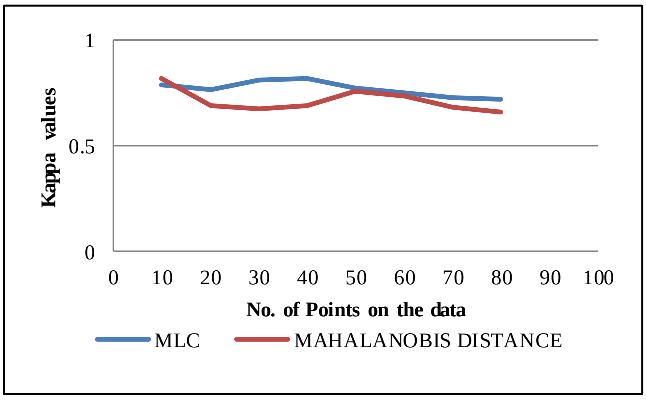

Fig. 5. Graph showing the variation of Kappa values with respect to the number of points selected on the data, for Table IV.

It can be seen from TABLE III and TABLE IV that, for 11 classes and 8 classes per pixel, both the classifier algorithms produce similar results. But, by taking the average of the classification accuracy, it can be seen that MLC again produces best classification results over the data considered. This can be more clearly seen in the Graphs illustrated in Fig.4 and Fig.5.

Table V and Table VI indicate the Overall Classification Accuracy and Kappa values when the Number of Classes is 11 and Number of Classes per pixel is 10.

Table V. overall classification accuracy values when the number of classes is 11 and number of classes per pixel is 10.

No. of points selected	Maximum Likelihood Classification	Mahalanobis Distance Classification
10	90.00%	90.00%
20	80.00%	90.00%
30	80.00%	86.67%
40	82.50%	72.50%
50	82.00%	72.00%
60	83.33%	75.00%
70	85.71%	78.57%
80	85.00%	80.00%

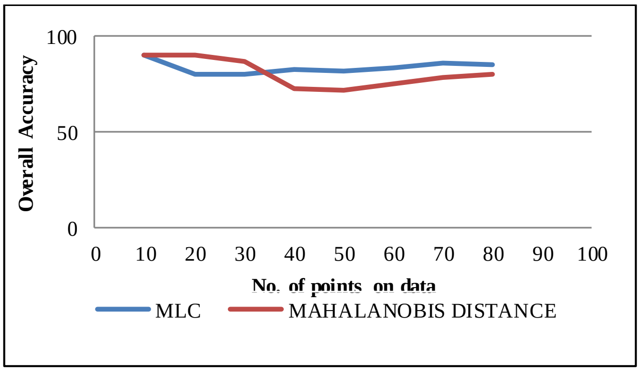

Fig. 6. Graph showing the variation of accuracy values with respect to the number of points selected on the data, for Table V.

Table VI. Overall kappa statistics when the number of classes is 11 and number of classes per pixel is 10.

No. of points selected	Maximum Likelihood Classification	Mahalanobis Distance Classification
10	0.4737	0.8529
20	0.5980	0.8606
30	0.6791	0.8209
40	0.7046	0.6565
50	0.6871	0.6468
60	0.6809	0.6749
70	0.7230	0.7130
80	0.7323	0.7270

It can be seen from Table V and Table VI that, for 11 classes and 10 classes per pixel MLC again produces best classification results over the data considered. Table VII indicates the summary of all the results that are obtained for class category indicating the average values of both overall classification accuracy and the overall Kappa statistics.

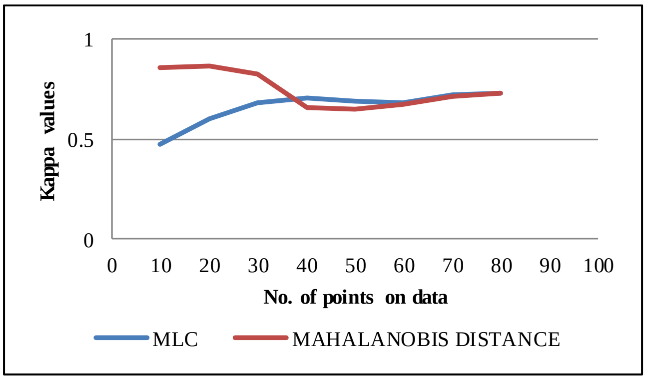

Fig. VI. Graph showing the variation of Kappa values with respect to the number of points selected on the data, for TABLE 6.

Table VII. Overall classification results for class 12 category.

NO. of Classes	No. of classes per pixel	Classification method used	Average of overall classification accuracy (%)	Average of overall kappa statistics
11	5	MLC	84.14%	0.7694
		MAHALANOBIS DIST	79.39%	0.6997
	8	MLC	89.277%	0.7693
		MAHALANOBIS DIST	84.1575%	0.7138
	10	MLC	83.5675%	0.6598
		MAHALANOBIS DIST	80.5925%	0.744

Conclusions

Analysis of the results indicates that application of Fuzzy Logic makes the RS image classification more complex. It is because of the type of the data used for classification. Since we have used a 23.5m resolution data, which is considered as low resolution data, both methods produce reasonably high accuracy value. It is hard to come to a conclusion by visually examining the classified images. Hence accuracy assessment is carried out for numerically finding which classification method results in highest accuracy value.

For the case of 11 classes and 5 classes per pixel, MLC produces highest accuracy value. Again, as the number of classes per pixel was varied to 8 and 10, MLC produces best accuracy results.

Hence, it can be concluded that, for the data considered and for 11 classes, Fuzzy based MLC produces best accuracy as compared to Mahalanobis Distance classification.

It should be noted that these results are correct only for the data obtained. In the study region, if there is a drastic change such as Industrial expansion, human settlement activity or Deforestation or Construction activity the nature of the data will change. Then the results definitely will vary.

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