IMPROVING PARALLELEPIPED CLASSIFICATION BY USING ELLIPTICAL SHAPE AND COMBINING MINIMUM DISTANCE IN MULTISPECTRAL IMAGERY

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Abstract. Parallelepiped decision is one of the simplest and fastest methods in supervised classification. Although the parallelepiped approachcould be implemented easily, it is not capable of separating pixels fallen into overlapping parallelepiped, or fallen outside any parallelepiped. For classifying pixels which are beyond the parallelepiped we have to expand borders and it willresultemerging inseparable pixels. In this paper we introduce two simple ways to resolve mentioned problems. Firstly, instead of rectangle we utilize ellipse inscribed in rectangle in order to reduce inseparable pixels. Secondly, we implement minimum distance for inseparable and outside pixels.In order to evaluate the proficiency of this method, the classes derived fromit and singleminimum distance have been compared to Maximum likelihood classifier subsequently. The results demonstrate that this method is more accurate and efficient than simple parallelepiped and single minimum distance.

INTRODUCTION

Supervised classification is the procedure most often used for labeling the pixels in image as presenting particular type of land use/land cover.

Various approaches have been proposed to perform this procedure. Despite of theirs variety we could categorize them in three main types:

1. Parametric: procedures have been based upon an assumption that the classes can be modeled by probability distributions and, as a consequence, are described by the parameters of those distributions [1]. For instance: Maximum likelihood, Minimum distance, Parallelepiped and etc.
2. Non-parametric: approaches which neither distribution models nor parametric are relevant. Neural networks and support vector machine (SVM) can be regarded as this kind of classification.
3. Non-metric: ways that based on empirical decision, using threshold for density slicing or building decision tree are common procedures for this type of classification.

Advantage and disadvantage of Parallelepiped classification

Parallelepiped classifier is the decision boundaries form an n-dimensional parallelepiped in the image data space. The dimensions of the parallelepiped classification are defined based upon a standard deviation threshold from the mean of each selected class. Each pixels fallen into one box will be labeled as defined class. The figure 1 represents this method:

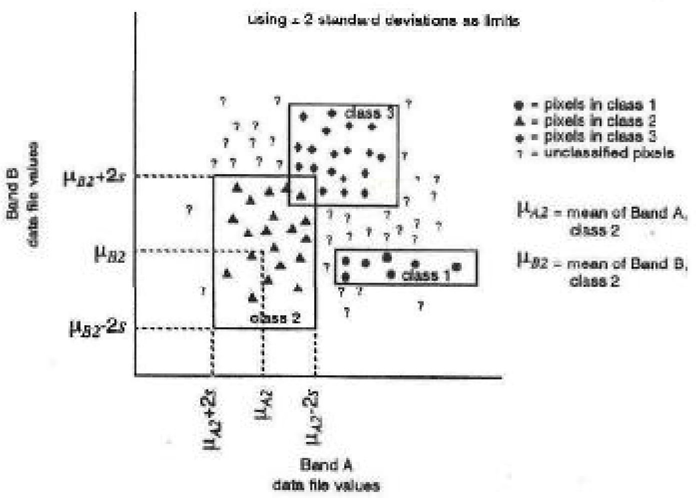

Fig.1. Parallelepiped classification

The main advantage of this decision is classifying simply and quickly, since the data file values are compared to limits that remain constant for each band in each signature. This method has three major problems:

- It cannot classify pixels existed in overlapping boxes.
- Many of pixels could be unclassified due to be fallen outside of boxes.
- Parallelepipeds have "corners" and some pixels may be classified which are actually quite far, spectrally, from the mean of the signature.

Figure 2 can illustrate the third problem clearly.

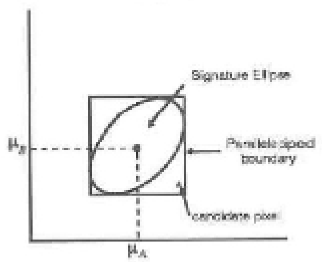

Fig.2. Parallelepiped corners

In spite of its shortcoming, this method has been widely applied for first-pass classification. This paper takes a new look at this method by altering the shape of the box into elliptical shape and implementing minimum distance for inseparable and outside pixels.

METHODOLOGY

Study Area and used data

In order to analyze the capability of this method, A Data set from LANDSAT ETM+ with 6 bands, has been provided which is located innorth of Iran. This data has a preference for evaluation because many kinds of land-use/land-cover could be distinguished. The study area is shown in figure 3:

Fig.3. Case study: LANDSAT composite image in north of Iran

Applying Elliptical shape

The size of boxes in parallelepiped method is adjusted to a coefficient (×2) multiply by standard deviation of ROI* from average of selected pixels. If we want to inscribe an ellipse in rectangle in two bands, the one-half of major and minor axes will be same as $k\sigma_A$ and $k\sigma_B$ respectively. Figure 4 indicates inscribed ellipse in rect.

Fig.4. Inscribed ellipse in rectangle in two bands

The Eq1 reveals the formula of inscribed ellipse:

$$\frac{(x-\mu_A)^2}{(k\sigma_A)^2}+\frac{(y-\mu_B)^2}{(k\sigma_B)^2}=1 \qquad (1)$$

Where σ_A and $\sigma_B$are standard deviation of selected pixels in band A and band B and μ_A and μ_B are average of selected pixels in band A and band B. K is adjustable for altering the size of parallelepiped.

For creating ellipse shape in more than two bands we will have "Hyper-ellipse" which can be constructed as Eq2:

$$\frac{(x-\mu_A)^2}{(k\sigma_A)^2}+\frac{(y-\mu_B)^2}{(k\sigma_B)^2}+\frac{(z-\mu_C)^2}{(k\sigma_c)^2}+\cdots=1 \qquad (2)$$

We have devised a procedure that can achieve two important aims:

- Reducing inseparable pixels

* Region Of Interest

- Avoiding classifying pixels which are far from mean of signature (corner problem)

Implementing Minimum distance for inseparable and outside pixels

As mentioned earlier, parallelepiped decision could not separate pixels fallen into overlapping boxes or fallen outside boxes. In this paper the minimum distance is implemented for thissolution.

Minimum Distance method

In this method, training data is used only to determine class means; classi cation is then performed by placing a pixel in the class of the nearest mean. The equation for classifying by spectral distance is based on the equation for Euclidean distance. The following figure can illustrate this approach.

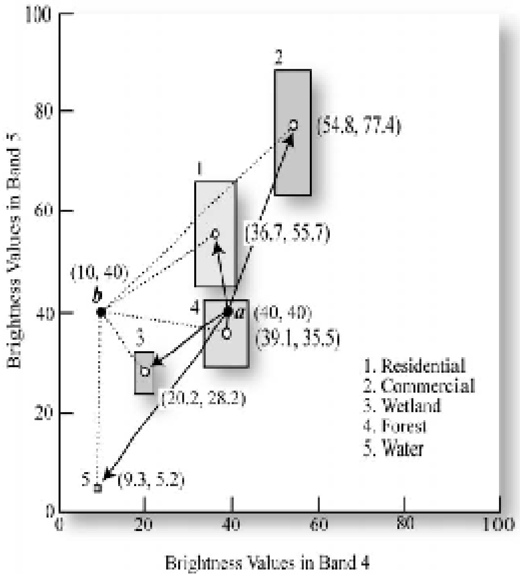

Fig.5. Pixel “b” will be classified as Wetland by minimum distance method

Program code

```
for i=1:rowofimage
for j=1:columnofimage
     k=0;
for q=1:numberofclass
d(q)=computing distance from pixel value to average of classes
if (pixel value is in hyper ellipse)  %using equation-2
k=k+1;
Save class
end
end
if k>1 (pixel is being known as inseparable pixel) or k==0 (pixel is being known as unclassified pixel)
findminimumdistanceof“d”
   Save class
end
end
end
```

EXPERIMENTS

Inseparable pixels appear when a training region includes more than one class. In order to evaluate the capability of the method, three regions included water, soil and vegetation have been selected *indiscriminately*. These ROIs are depicted in figure 6.

Fig.6. ROIs which are selected carelessly (blue: water, green: vegetation, magenta: soil)

2-D scatter plot (see fig 7) can clearly demonstrate that how this method decrease inseparable pixels efficiently in classification of soil and vegetation areas.

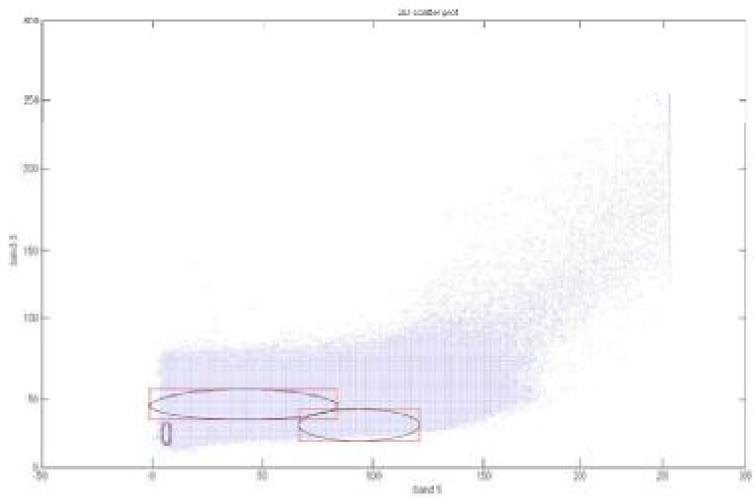

Fig.7. Scatter plot of pixels and ellipses in band 5 and 3

The proficiency of this method can be examined by comparing introduced approach, single minimum distance and simple parallelepiped to Maximum likelihood classifier. 8 fixed classes have been selected for training data. The selected classes also have been shown in 2-D visualizer that x axis is DNs in band3 and y axis is DNs band5. (See figure 8).

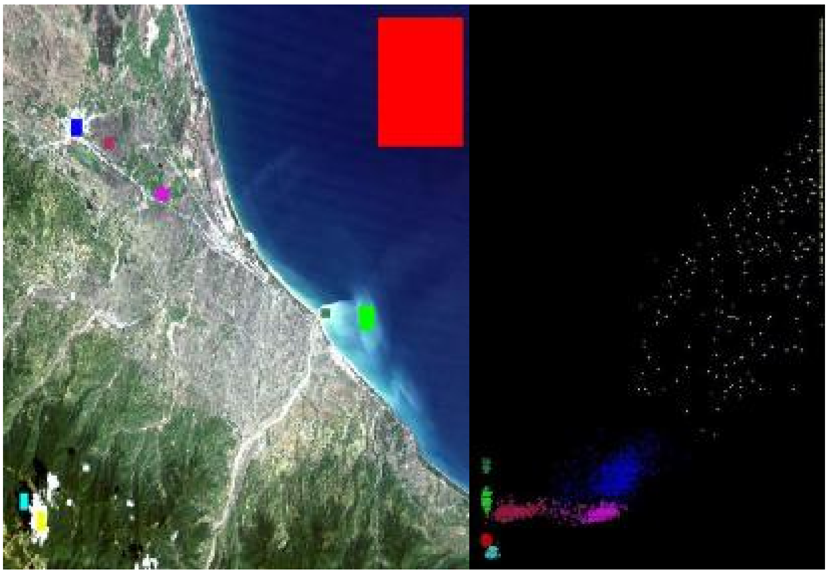

Fig.8. *Left*: 8 selected ROIs *Right*: 2-D visualizer of selected pixels in band 5(x axis) and band 3(y axis)

After classifying our case study the ellipses inscribed in rectangles will be formed. The K parameter is “3” and it was fixed during the classification. The figure 9 illustrates these ellipses in band 5 and 3; classified images by Minimum distance, Maximum likelihood, the new approach and simple parallelepiped are depicted in figure 10.

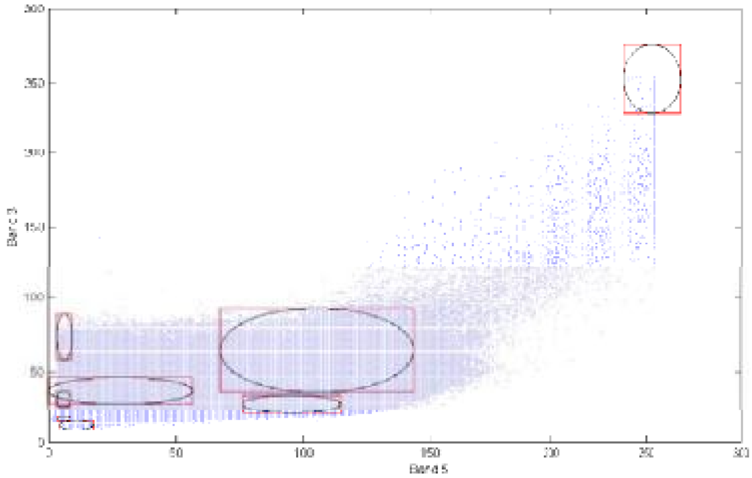

Fig.9. Inscribed ellipses in band 5 and 3.

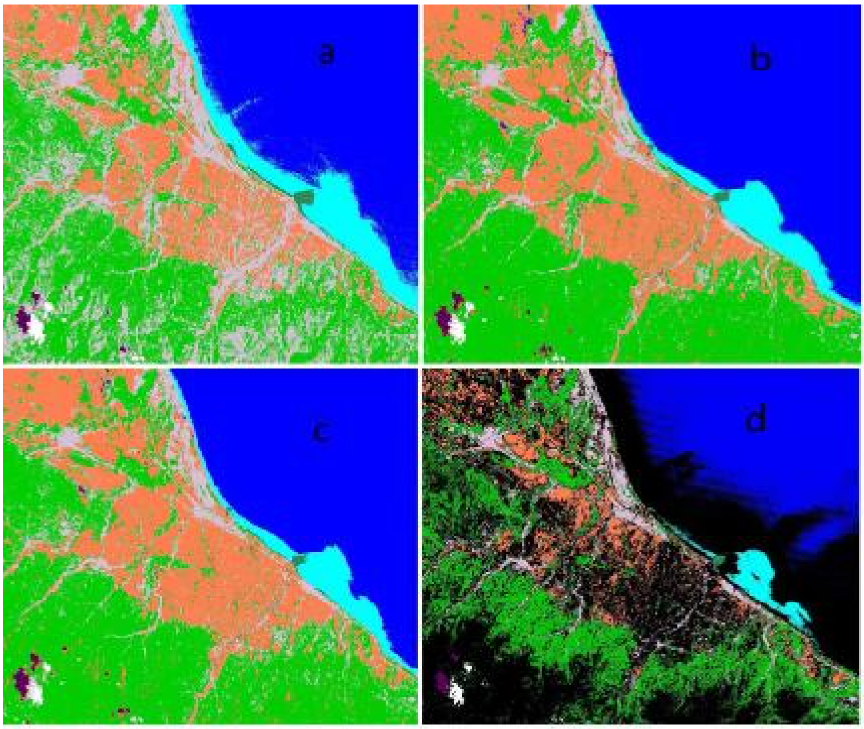

Fig.10. Classified image by: a) maximum likelihood b) minimum distance c) the proposed method d) simple parallelepiped

In simple parallelepiped classification the black areas are unclassified pixels. The classified image which derived from maximum likelihood classifier has been considered as *truth ground* image because by paying attention to figure8 we can assume that the classes are based on normal distribution. In maximum likelihood classi cation each class is modeled by a multivariate normal class model that can account for spreads of data in particular spectral directions. Since covariance data is not used in the minimum distance technique, classmodels are symmetric in the spectral domain. Elongated classes therefore will not be well modeled in minimum distance approach. [1] After creating confusion matrix, the overall accuracy and kappa coefficient have been computed in the table 1.

Table 1. the evaluation of accuracy.

	Overall accuracy	Kappa coefficient
The Proposed Approach	81.6273%	0.7670
Minimum Distance	78.7472%	0.7253
Simple Parallelepiped	45.5455%	0.3869

CONCLUSION

The marked observation which emerged from the data comparison was that the proposed method can classify pixels more accurate than minimum distance and simple parallelepiped. Given that the parallelepiped decision is based on “standard deviation” and “mean”, the size of boxes is intensively sensitive to training area.The ROI’s should consequently be selected with the utmost caution. Therefore if a training data does have integrated classes, without any doubt the results will be erroneous. Although approximately 3% difference between minimum distance and proposed approach does not seem significant, in this area 3% includes over 43718 pixels which cover 3550 hectares. We believethis approach will pave the way for inventing hybrid classifiers which can diminish the disadvantage of single classifiers.

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