Detection of Environmental Changes through Supervised Classification

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Abstract

Nowadays, satellite based remote sensing technology has been successfully utilized for mapping, monitoring and detection of environmental changes. The interested information will be extracted from satellite images by using Digital Image Processing. In this paper, the environmental changes due to natural hazards can be detected and monitored using supervised classification. To extract the information from the multi-date images, the Minimum Distance classifier (MD) is used to identify the classes of images based on RGB color values. It is used in training and also in recognition. The Minimum distance classifier which is based on training data characterizes each class by its mean position on each band. The classification is performed by placing a pixel in the class of the nearest mean. The main purpose of this paper is to evaluate and compare the satellite images of before and after natural disasters in the world with results from the supervised training based methods.

keywords: Remotely sensed image, Image Classification, Change detection, Minimum distance classifier

1. Introduction

In recent ten years, there have existed the significant environmental changes, especially in a country covered by monsoon climate as a tropical area. Floods are annual occurrences over many countries in all over the world [1].

Remote sensing technologies have been used to study disaster management for the last 2 decades. Remote sensing is a science of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the objects [2].

Satellite imagery would be the best resources due to its temporal frequency and wide spatial coverage. Image classification is an important part of the remote sensing and image analysis.

At present, there is different image classification procedures used for different purposes in two main ways as supervised and unsupervised classifications. Additionally, supervised classification has different sub-classification methods which are named as parellelpiped, maximum likelihood, minimum distances, fisher classifier methods, etc.

One of the most widely used pattern recognition techniques is classification based on maximum likelihood (ML) assuming Gaussian distributions of classes. A problem of Gaussian ML classification is long processing time [3].

Another possible approach to reduce computing time can be found in decision tree classifiers. One of the advantages of the decision tree classifier is processing time. However, how to find the optimum tree structure still remains a problem for the decision tree classifier, though many algorithms are proposed for the design of decision tree classifiers [4].

In this paper, Minimum Distance classifier is used to classify the multi-date satellite images. The MD classification uses the mean vectors of each region of interest (ROI). It calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the closest ROI class unless the user specifies standard deviation or distance thresholds, in which case some pixels may be unclassified if they do not meet the selected criteria.

System implementation is explained in Section 2. Algorithms are presented in Section 2.2 and 2.3. Experimental results are shown in Section 3. Section 4 is about the conclusion of paper.

2. System Implementation

The system consists of five steps: preprocessing, defining and training the class, classify with minimum distance classifier, compare output classified images of before and after disasters and output change detected images.

In this paper, the false color images formed from the combination of infrared and visible light, are used. The satellite images showed flooding areas around the world are acquired from MODIS (NASA) sensor.

To get higher-quality change detection results, we have to minimize any other noise factors by selecting multi-temporal image pairs that have similar photographing conditions, such as atmospheric conditions, variation in the solar illumination angles, and sensor calibration trends.

The flow diagram is shown in figure 1.

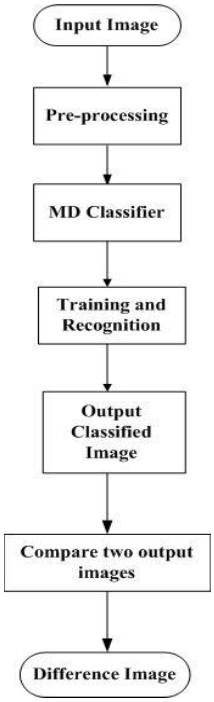

Fig1. System Design

2.1. Preprocessing

The first preprocessing step is cropping the desired region from the original image and defining the areas that will be used as training sites for each land cover class. This is usually done by using the on-screen digitized features. For this purpose, band is chosen with strong contrast (such as a near infrared band) or a color composite image for use in digitizing.

2.2. Minimum Distance Classification (MD)

The Minimum Distance to Mean (MD) method is a supervised classification method that first analyzes the training data and calculates a mean vector for each prototype class. MINDIS Classifier performs multispectral classification of image data for up to 256 classes based on Euclidean distance [5]. This method calculates the center for each group of pixels and measures the distance from the center of each group to the pixel being considered. The pixel is classified to the group with the nearest center. The pixels are assigned to a specific class if they fall within the box regions, which are defined by the training data, and are allocated to the appropriate categories [6]. The center of the group then is recalculated each time a pixel is added or taken away. All pixels are classified to the closest class unless the user specifies standard deviation or distance thresholds, in which case some pixels may be unclassified if they do not meet the selected criteria.

Feature vector is computed for these samples again and a distance Euclidean is used to classify the unknown samples.

Minimum Euclidean distance:

$$D_j(x) = || x - m_j || \quad for\ j = 1, 2, \ldots, M \qquad (1)$$

x is the feature vector to be classified, m is the mean value of the training vectors, m is the transpose.

$$G_i(X) = (X-U_i)^T * (X-U_i)$$
$$= SUM\ [(x_j-u_j)**2] \quad \text{for } j = 1 \text{ to } d. \quad (2)$$

$G_i(X)$ is the result for class i on pixel X. T indicates transposition of the elements in brackets. d is the number of channels in the classification. X $(x_1,..,x_d)$ is the (d by 1) pixel vector of grey-levels. U_i $(u_1, ..., u_d)$ is the (d by 1) mean vector for class i. j is the subscript of j^{th} element of a vector. SUM [ ] is the total of elements inside brackets.

The distances between the pixel to be classified and each class centre are compared. The pixel is assigned to the class whose centre is the closest to the pixel. If for all i not equal j, $G_j(X) < G_i(X)$, then X is classified as j.

2.3. Change Detection

Change detection technology is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Change detection is an important process in monitoring and managing natural resources and urban development, environmental inspection, forest policy, disaster damage, updating of geographical information and the military usage. A variety of change detection techniques can be grouped into two main categories**:** post classification comparison techniques and enhancement change detection techniques. In this paper, image differencing, one of the enhancement change detection techniques, is used. The enhancement change detection techniques have the advantage of generally being more accurate in identifying areas of spectral change.

2.3.1. Enhancement Change Detection Techniques

Enhancement techniques involve the mathematical combination of images from different dates which, when displayed as a composite image, show changes in distinctive colors. The enhancement techniques have the advantage of generally being more accurate in identifying areas of spectral change. The three enhancement change detection techniques are Image differencing, principal component analysis and change vector analysis.

2.3.2. Image Differencing: Image differencing is a technique by which the first image that have pixel digital number values for one band subtracted from the corresponding pixel digital number values from the same band in the second image to produce a residual image, which represents the change between the two dates. The two images are registered images and acquired at different times. The subtraction results in positive and negative values in areas of surface change and zero value in areas of no change. Due to its simplicity, image differencing is a popular method for change detection. An important consideration in using this technique is how to decide where to place the threshold for change in the differenced image. This method is based on the signed difference image:

$$D(x) = I_2(x) - I_1(x). \tag{3}$$

The change mask B(x) is generated according to the following decision rule:

$$B(x) = \begin{cases} 1, & \text{if there is a significant change D(x) at pixel x} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The difference map is usually binarised by thresholding it at some pre-determined value to obtain a change or no-change classification. However, the threshold value is critical, since too low value will swamp the difference map with spurious changes, while too high value will suppress the significant changes.

3. Experimental Results

Before and after disaster images from two dates are used as input images. The images are firstly cropped to extract the desired regions. Users need to define the model classes from interested region to classify the images. This experience can estimate three feature types of remotely sensed image. In this paper, these three features: water, bare soil and vegetation are classified in both two-date satellite images using MD classifier. The classified output image indicates environmental change regions in percentage.

Figure 2 (a) and (b) show the original image of China before and after flooding affect. The four classes: water region, land (vegetation), bare soil and urban are selected as the classified data.

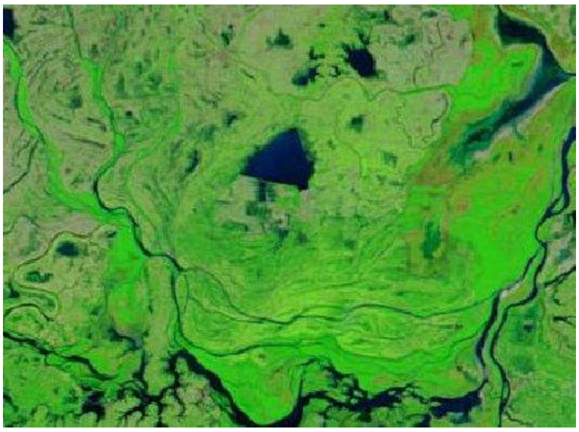

Fig 2. The Original image
(a) Before flooding in China

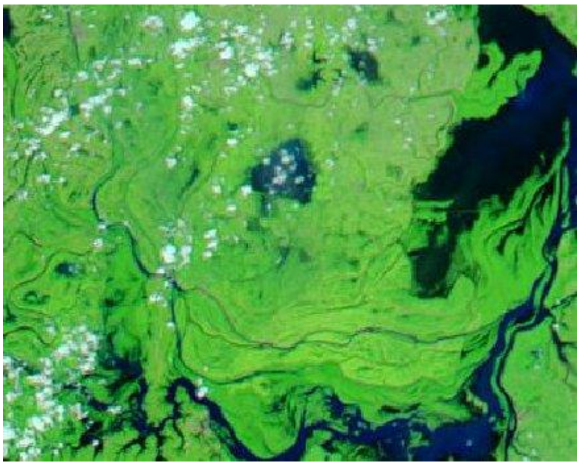

Fig 2. The Original image
(b) After flooding in China

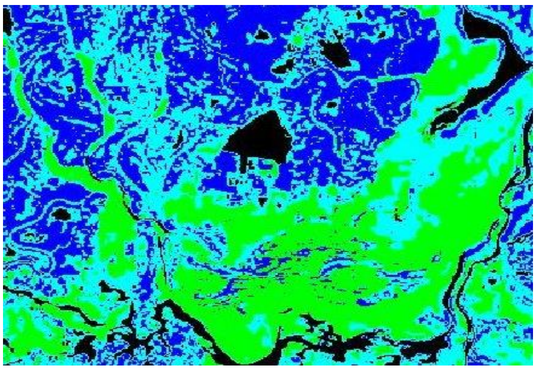

Fig 2.(c) Output classified image of before flood

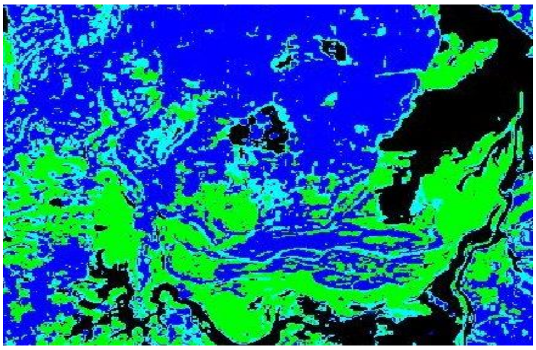

Fig 2. (d) Output classified image of after flood

Figure 2 (c) and (d) show the classified results with four classes.

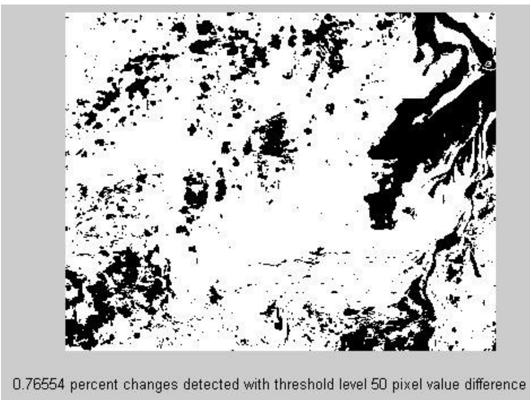

Fig 2. (e) Detection of environmental changes (difference image at threshold 50)

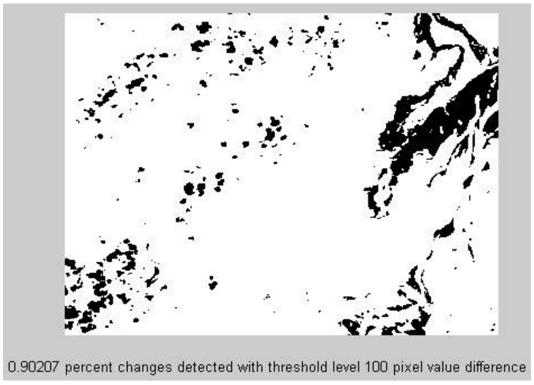

Fig 2. (f) Detection of environmental changes (difference image at threshold 100)

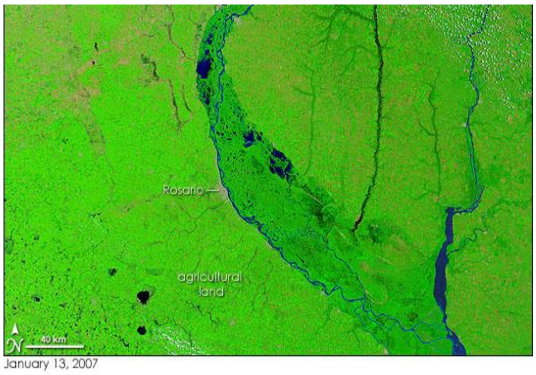

Fig 3. The original image
(a) Before flooding in North Argentina

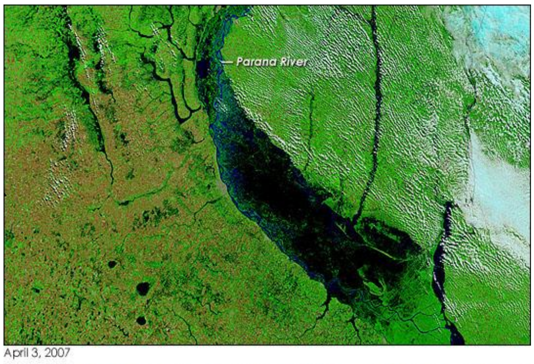

Fig 3. The original image
(b) After flooding in North Argentina

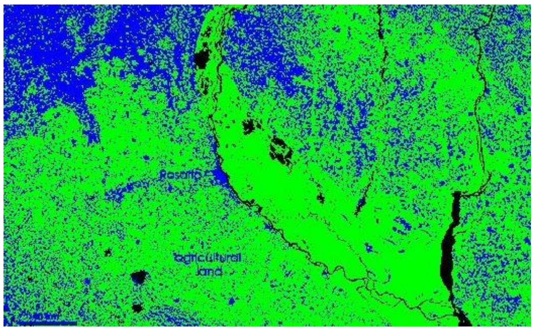

Fig 3. (c) Output classified image of before flood

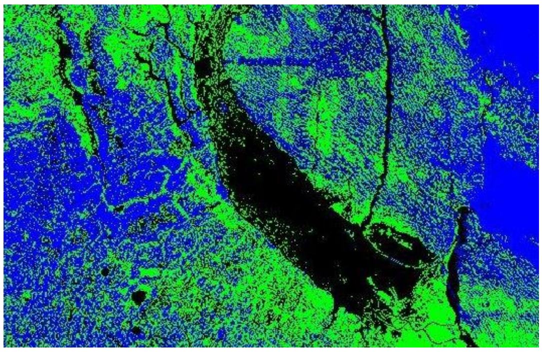

Fig 3. (d) Output classified image of after flood

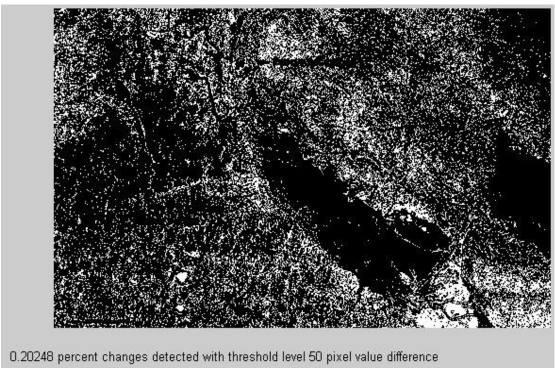

Fig 3.(e) Detection of environmental changes (difference image at threshold 50)

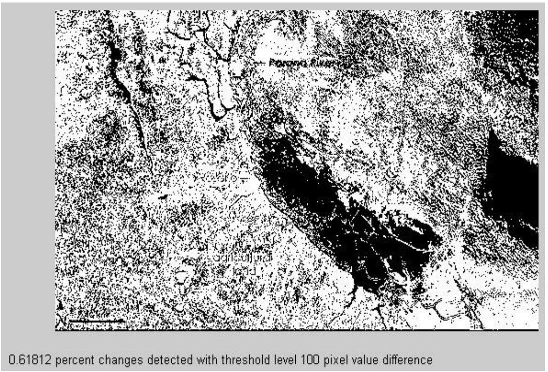

Fig 3.(f) Detection of environmental changes (difference image at threshold 100)

The system has been tested on a number of images. The result from the classified image is estimated as percentage of the whole image area. This is shown in the table 1 and 2.

Table 1. Classified results from the two-date images

Images	water	land	bare	urban
China fig 2(c)	8.17 %	25.23 %	27.65 %	38.92 %
China fig 2(d)	17.01 %	23.15 %	41.77 %	18.05 %
Changes at threshold 50			0.76554 %	
Changes at threshold 100			0.90207 %	

Table 2. Classified results from the two-date images

Images	water	land	bare
North Argentina fig 3(c)	3.07 %	69.63 %	27.29 %
North Argentina fig 3(d)	21.5 %	36.49 %	41.98 %
Changes at threshold 50		0.20248 %	
Changes at threshold 100		0.61812 %	

4. Conclusion

Flood disaster is a common problem in the world. Effective flood assessment systems after flooding will help plan and execute post disaster relief measures efficiently. Results of this work could be helped the scientists to look and study the environmental changes that could affect the globe in the future conditions like pollution, global climate change, natural resource management, urban growth, and much more trend across large geographic areas.

The limitations of system are that the two-date images must be situated in the similar location and are equal in image dimension. Moreover, cloud cover during the rainy season can be so extensive that obtaining a cloud-free view of every pixel of the area may not be possible. Users need to define the model classes from interested region to classify the images.

The system has been tested on a number of images. All performed image classifications give good results. The classification performance was tested at various threshold values. The amount of threshold value was increased as the detection of changes was more significant. The *minimum distance to means* classifier is fast, computationally simple commonly used and suitable for change detection applications.

5. References

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