



Study of Local Kernel with Fuzzy C Mean Algorithm

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Abstract – Remote sensing has become one of a new and interesting area in the field of computer science. Today we have to handle a large amount of remote sensing images to obtain information concerning land cover mapping. Image classification is one of the important process in this field. Effectual use of different features of remotely sensed data and the selection of suitable classification method are especially important for improving classification accuracy. This paper explains how remote sensing data with uncertainty are dealt with fuzzy based classification using kernel approach. Here we mainly study FCM with local kernels.

Keywords – Image classification, Remote sensing, Fuzzy logic, Kernel Method, local Kernel.

I. INTRODUCTION

The aim of multispectral image used in image sensing images is to classify all the pixels automatically in image categories representing land cover, which means conversion of image data to information of a certain induction. Through image classification we extract the information about various land cover classes from remote sensing data and assign a class membership to each pixel. In classification of images we could use hard classifiers or soft classifiers. In hard classification each pixel belong to one class only while in soft classification membership value is assigned to each pixel that is how much each pixel belong to each class. Fuzzy classification is used where mixed pixel may be assigned membership values. For this purpose supervised or unsupervised approach may be used.

In this research work we will study how remote sensing data with unpredictability are handled with fuzzy based classification using kernel approach for land use/land cover map generation. The use of fuzzification using kernel approach provides the basis for the development of more robust approaches to the remote sensing classification problem. The kernel method absolutely defines the similarity measure between two samples and implicitly represents the mapping of the input space to the feature space.

II. IMAGE CLASSIFICATION

Remote sensing is a wide new exciting field of computer science with adequate development in recent years. Over two dozen optical satellites are currently in orbit performing earth imaging.

Image classification is a procedure of classifying multispectral images into patterns of varying gray or assigned colours that represent either cluster of statistically different sets of multiband data, some of which can be correlated with separate classes or features or materials. This is the result of unsupervised classification or numerical discriminators composed of these sets of data that have been grouped and specified by associating each with a particular class, etc whose identity is known independently and which has representative areas within the image where that class is located. Image classification can be taken as a useful representation in most of decision problems, simplifying information by means of an informative scheme of the main issues to be taken into consideration.

Classification is commonly done one by one on image, obtaining training areas for each individual image and then performing supervised hyper spectral classification of the image.

The information contained in image allows the characterization, identification, and classification of land covers with improved accuracy and robustness. In remote sensing, many supervised and unsupervised methods have been developed for multi-spectral image classification (e.g. maximum likelihood classifiers, neural networks, etc.).

III. Fuzzy C-Means Approach (FCM):

Fuzzy C-Means (FCM) was originally introduced by J. C. Bezdek ([1], [2]). In this clustering technique each data point belongs to a cluster to some degree that is specified by a membership grade, and the sum of the memberships for each pixel must be unity. This can be achieved by minimizing the generalized least – square error objective function,

$$J_m = \sum_{i=1}^N \sum_{j=1}^c (\mu_{ij})^m \|d_i - c_j\|^2, 1 \leq m \leq \infty \quad \dots (1)$$

Where, N is the total number of pixels, c is the number of classes, μ_{ij} is the fuzzy membership value of i^{th} pixel for class j, m is the fuzzy weight; which controls the level of fuzziness, d_i is a vector pixel value and c_j is the mean vector of cluster j. The membership value μ_{ij} satisfies the following constraints [2]:

$$0 \leq \mu_{ij} \leq 1; i \in \{1, \dots, N\}, j \in \{1, \dots, c\} \quad \dots (2)$$

$$\sum_{j=1}^c \mu_{ij} = 1; i \in \{1, \dots, N\} \quad \dots (3)$$

$$\sum_{i=1}^N \mu_{ij} > 0; j \in \{1, \dots, c\} \quad \dots (4)$$

In FCM, the membership value is calculated with the help of following equation ([3], [4])

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{x_{ij}^2}{x_{ik}^2} \right)^{1/(m-1)}}; i \in \{1, \dots, N\}, j \in \{1, \dots, c\} \quad \dots (5)$$

Where, $x_{ik}^2 = \sum_{j=1}^c x_{ij}^2$ and $x_{ij}^2 = \|d_i - c_j\|^2$ [3]. In FCM clustering technique, it is necessary to determine the value of m, being the degree of fuzziness, in equation (1). If the value of m=1 then it is essentially the hard clustering [2]. Foody [5] states that in most of the clustering cases m=2.0 produce the most accurate fuzzy classification, therefore in this study m=2.0 were taken.

The fuzzy set theory shows a powerful instrument in designing efficient tools to process remote sensing images and also to support the spatial decision making process.

IV. KERNEL METHODS

Kernel method show excellent performance in multispectral data classification in terms of accuracy and robustness. The properties possessed by kernel method make them well-suited to tackle the problem of multispectral image classification since they can handle large input spaces effectively, work with a relatively low number of labelled training samples, and deal with noisy samples in a robust way. Kernel-based methods are based on mapping data from the original input feature space to a kernel feature space of higher dimensionality, and then solving a linear problem in that space. By replacing the inner product with an appropriate kernel function, one can implicitly perform a non linear mapping to a higher dimensional feature space without increasing the number of parameters. Kernel methods show the ability to handle with the nonlinear models by mapping a given problem from the (low dimensional) input space onto a new (higher dimensional) space via a nonlinear transformation. The resulting structure of the classification task is then linearly separable.

V. KERNELS IN FCM

In this the kernel function is constructed by FCM algorithm to map the training data set into a higher dimensional space when the linear separation is impossible in the original one. FCM can be generalized to calculate non linear decision surfaces[6]. The method consists in projecting the data in a higher space where they are considered to become linearly separable. FCM applied in this space lead to the determination of nonlinear surfaces in the original space. This projection can be simulated using kernel method.

A various number of kernels prevail and it is difficult to explain their individual characteristics. The kernels used in work here are local kernels, which are mentioned as follows:

Local kernels: Only the data that are close or in the proximity of each other's had an influence on the kernel values. Basically, all the kernels that are based on distance function are local kernels. Examples of typical local kernels used in this are:

KMOD:

$$K(x_i, x_j) = \exp\left(\frac{1}{1+\|x_i-x_j\|^2}\right) - 1$$

Inverse Multiquadric:

$$K(x_i, x_j) = \frac{1}{\sqrt{\|x_i-x_j\|^2+1}}$$

These local kernels along with FCM are used for the classification of remote sensing images for nonlinear distribution of data.

VI. KERNEL BASED MULTI-SPECTRAL IMAGE CLASSIFICATION

In this study classification of multispectral data with high resolution from urban areas by combining hierarchical image segmentation and kernels with Fuzzy C Mean (FCM) is investigated. The pixel-based classification was carried out by merging structural details from mathematical morphological profile. FCM along with local kernels was used and studied to classify remote sensed image. Here a java tool is developed which classify the images using FCM with local kernels. The per-pixel classification results obtained and the hierarchical image segmentation results obtained were finally combined for object-based image classification by a multi-level overlay operation. The results obtained showed that the proposed classification method shows higher image classification accuracy, compared to per-pixel spectral classification.

VII. RESULTS

In this research work we develop a java tool for image classification using FCM with kernel method implementing local kernels KMOD and Inverse Multiquadric. Its results are shown in figures below. The image in (Fig.1) shows the original satellite image which has been classified using the tool:

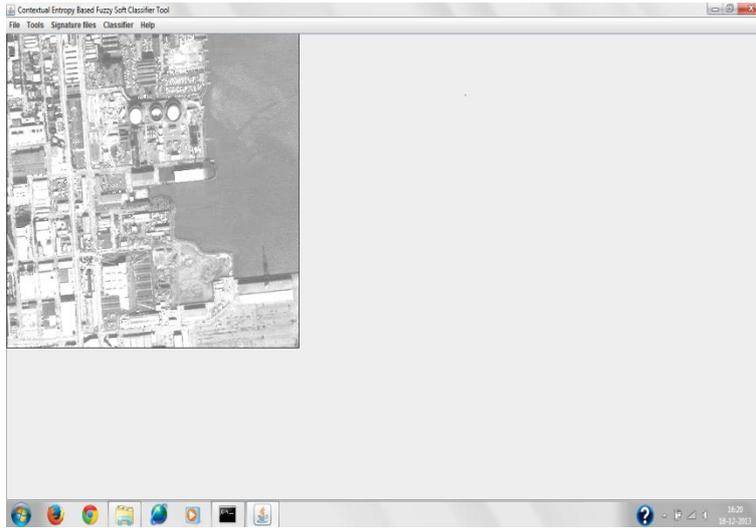


Fig. 1 Original satellite image

This image after being classified by the tool implementing FCM with local kernels shows the output as shown in figure (Fig. 2) and (Fig. 3):

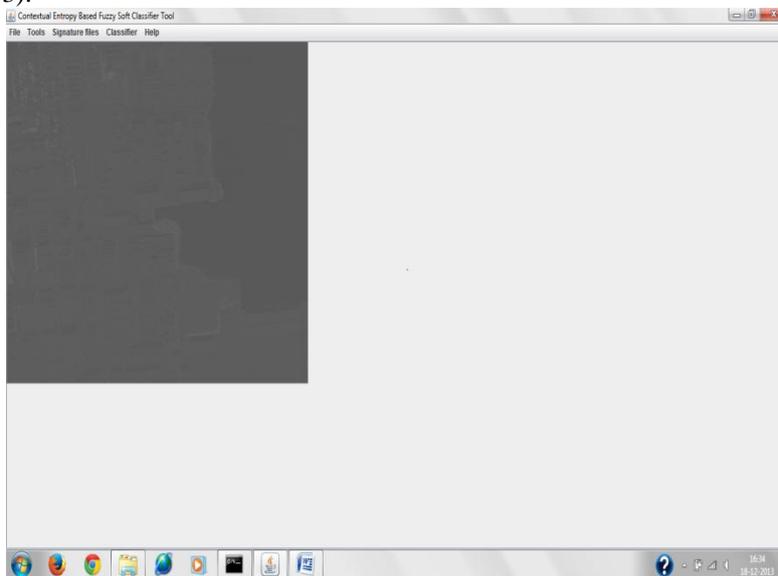


Fig. 2 Image classification showing vegetation class

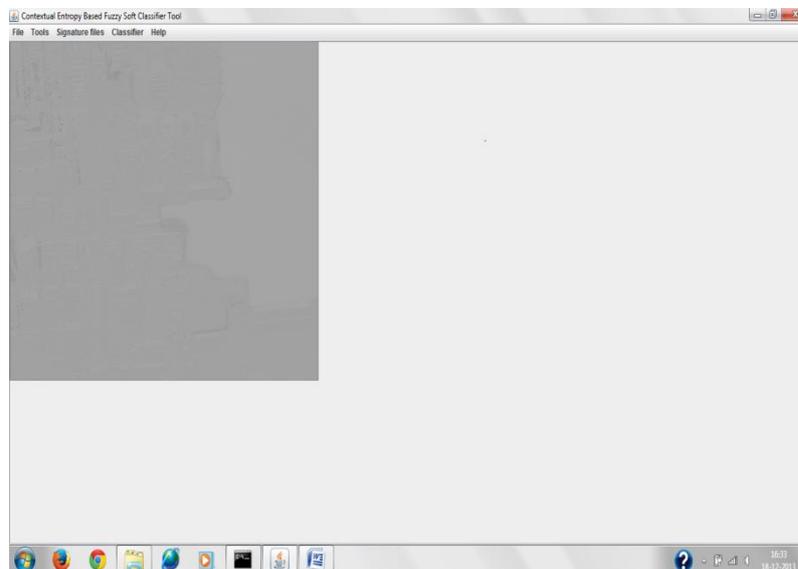


Fig. 3 Classification of image showing water class

In this study we have taken the original satellite image as in (Fig. 1) and taken two classes in it one vegetation and one water class. Then the classification results are as shown in (Fig.2) and (Fig. 3). The portions where it is more white shows it has more membership value and belongs to that class as in (Fig. 2) it shows the vegetation class while in (Fig. 3) the white area has high membership value of water class.

Thus by our study of FCM with kernel method we are able to classify nonlinear data and produce much more robust and accurate results using local kernels along with FCM.

VIII. CONCLUSION

We have proposed an approach for classification of remotely sensed imagery with the help of kernel methods. All kernels that are based on a distance function are local kernels and in local kernels the data that are close or in the proximity of each other's have an influence on the kernel values. Kernel methods have the capability to handle nonlinear models by mapping a given problem from the (low dimensional) input space onto a new (higher dimensional) space via a nonlinear transformation. The resulting structure of the classification task is then linearly separable. It is proved by our study.

ACKNOWLEDGMENT

I acknowledge and express my deepest sense of gratitude to my IIRS supervisor Dr. Anil Kumar for his constant support, guidance and continuous encouragement. I highly appreciate his technical comments, suggestions and criticism during the progress of this research work. I also thank Dr. Y. V. N. Krishna Murthy, Director IIRS; Faculty of Geoinformatics division, Dr. S. K. Shrivastav, Shri. P. L. N. Raju for all the support and guidance provided by them.

I also thank my supervisor at University Mr. Pawan Kumar Mishra for his constant support and guidance.

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