Modified Adaptive Fuzzy C-Means Algorithm for Satellite Image Segmentation

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Abstract

This paper presents a generalized Modified Adaptive fuzzy C-means clustering (MAFCM) methodology satellite image segmentation. Satellite images often require segmentation in the presence of uncertainty, caused due to factors like environmental conditions, poor resolution and poor illumination. Since any subsequent image analysis depends on the quality of such segmentation, one has to obtain an efficient algorithm for the purpose. Pixel clustering is a popular way of determining the homogeneous image regions, corresponding to the different land cover types, based on their spectral properties. The proposed MAFCM algorithm provides us a new flexible vehicle to fuse different pixel information in image-segmentation problems. That is, different pixel information represented by different kernels is combined in the kernel space to produce a new kernel. It is shown that this algorithm performs better than the kernel fuzzy C-means clustering algorithm. Simulations are performed on the synthetic texture and satellite images to demonstrate the flexibility and advantages of MAFCM-based approaches.

Keywords: fuzzy C-means (FCM), image segmentation, kernel function, texture, satellite image.

1. Introduction

Image analysis is based on the extraction of meaningful information and can involve many steps, such as pre-processing (e.g. noise removing), segmentation and characterization of the identified objects [1]. Particularly, the identification of the types of objects, constitutes an essential issue in pattern recognition [1] due to its practical importance, such as in the treatment of images obtained from satellite prospection. In fact, image segmentation can be understood as the process of assigning a label to every pixel in an image, such that pixels with the same label represent the same object, or its parts. Segmentation algorithms can be classified into different categories based on segmentation techniques used such as the features thresholding [9], template matching [10], region based technique and clustering. Those techniques have their own limitations and advantages in terms of suitability, performance and computational cost. The low-level segmentation techniques are known to be fast and simple, but these methods simply analyze an image by reducing the amount of data to be processed. This problem can result in loss of important information. Moreover, the low-level segmentation techniques may incorrectly identify region or boundary of an object due to the distraction of noise in an image. Clustering, particularly fuzzy C-means (FCM)-based clustering and its variants, have been widely used in the task of image segmentation due to their simplicity and fast convergence [6], [8]. By carefully selecting input features such as pixel color, intensity, texture, or a weighted combination of these data, the FCM algorithm can segment images to several regions in accordance with resulting clusters. Recently, the FCM and other clustering-based image-segmentation approaches are improved by including the local spatial information of pixels in classical clustering procedures. In addition to the incorporation of local spatial information, the kernelization of FCM has made an important performance improvement [3], [5].

The kernel FCM (KFCM) algorithm is an extension of FCM, which maps the original inputs into a much higher dimensional Hilbert space by some transform function. After this reproduction in the kernel Hilbert space, the data are more easily to be separated or clustered. KFCM is applied in the image-segmentation problems, where the input data selected for clustering is the combination of the pixel intensity and the local spatial information of a pixel represented by the mean or the median of neighboring pixels. Chen and Zhang [4] applied the idea of kernel methods in the calculation of the distances between the examples and the cluster centers. They compute these distances in the extended Hilbert space, and they have demonstrated that such distances are more robust to noises. To keep the merit of applying local spatial information, an additional term about the difference between the local spatial information and the cluster centers (also computed in the extended Hilbert space) is appended to the objective function. Modified Adaptivemethods provide us a great tool to fuse information from different sources [7]. It is necessary to clarify that, in this paper, we use the term “multiple kernel” in a wider sense than the one used in machine learning community.

In this paper, we propose a general framework of MAFCM methodology. In the framework, besides the direct applications of various composite kernels in the KFCM, a new algorithm that uses a linear composite of multiple kernels is proposed and the updating rules of the linear coefficients of the combined kernel are obtained automatically. Object-oriented image classification is based on the fact that important semantic information necessary to interpret an image is not represented in single pixels, but in meaningful image objects and their mutual relations. A strong and experienced evaluator of segmentation techniques is the human eye/brain combination. By applying segmentation procedures to the automation of image analysis, the activity of visual digitizing is replaced. Recent applications of image segmentation and image understanding techniques require increased robustness, better reliability and high automation of the algorithms. The concept of heterogeneity (and homogeneity) is perhaps the key characteristic of every landscape and underlies the scale factor in images. It may be defined as the uneven, non-random distribution of ecological units. There are three types of heterogeneity: temporal, functional and spatial. In the image multi-scale segmentation, the quantitative criterion for the evaluation of the segmentation results is that the average heterogeneity of pixels is minimized. Each pixel is weighted with the heterogeneity of the image object

To which it belongs. The qualitative criteria are the fact that any segmentation results have to satisfy the human eye and the information, which can be extracted from image objects for further successful processing. With satellite remote sensing techniques now becoming the single most effective method for land cover/land use data acquisition, it is imperative that standardized, object-oriented approaches to image analysis be developed.

2. Satellite Image Segmentation Techniqus

2.1. Related Research

Multiresolution segmentation is a bottom up region merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into bigger ones. Throughout this pair wise clustering process, the underlying optimization procedure minimizes the weighted heterogeneity of resulting image objects, where n is the size of a segment and h an arbitrary definition of heterogeneity [3]. In each step, that pair of adjacent image objects is merged which stands for the smallest growth of the defined heterogeneity. If the smallest growth exceeds the threshold defined by the scale parameter, the process stops. Doing so, multi-resolution segmentation is a local optimization procedure. The entropy based methodology for segmentation of satellite images is performed as follows. Images are divided into square windows with a fixed size L, the entropy is calculated for each window, and then a classification methodology is applied for the identification of the category of the respective windows. The classification approach can be supervised or non-supervised. Supervised classification needs a training set composed by windows whose classes are previously known (prototypes), such as rural and urban areas.

2.2. Issues

When applying the KFCM framework in image-segmentation problems, the multiresolution segmentation may end up with local optimization procedure. Global mutual fitting is the strongest constraint for the optimization problem and it reduces heterogeneity most over the scene following a pure quantitative criterion. Its main disadvantage is that it does not use the treatment order and builds first segments in regions with a low spectral variance leading to an uneven growth of the image objects over a scene. It also causes an unbalance between regions of high and regions of low spectral variance. Comparison of global mutual fitting to local mutual fitting results show negligible quantitative differences, the former (local) always performs the most homogeneous merge in the local vicinity following the gradient of the degree of fitting. The growth of image objects happens simultaneously as well in regions of low spectral variance as in regions of high spectral variance.

3. Proposed Method

We propose a new version of kernel based segmentation technique, particularly for images with low resolution and reduced contrast. The application of multiple or composite kernels in the FKCM has its advantages. In addition to the flexibility in selecting kernel functions, it also offers a new approach to combine different information from multiple heterogeneous or homogeneous sources in the kernel space. Specifically, in image-segmentation problems, the input data involve properties of image pixels sometimes derived from very different sources. Therefore, we can define different kernel functions purposely for the intensity information and the texture information separately, and we then combine these kernel functions and apply the composite kernel in MAFCM to obtain better image-segmentation results. Examples that are more visible could be found from multitemporal remote sensing images. The pixel information in these images inherits from different temporal sensors. As a result, we can define different kernels for different temperature channels and apply the combined kernel in a Modified Adaptivelearning algorithm.

Given a data set X = {x1,x2,…….x_n}, where the data point $\mathbf{x}_j \subseteq R^p$(j = 1, . . . , n), *n* is the number of data, and *p* is the input dimension of a data point, traditional FCM [3] groups *X* into *c* clusters by minimizing the weighted sum of distances between the data and the cluster centers or prototypes defined as

$$Q=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}\left\|x_j-o_i\right\|^2 u_{ij}^{m}u_{ij}$$

Here, $\| \ \|$ is the Euclidean distance. u_{ij} is the membership of data x_j belonging to cluster *i*, which is represented by the prototype o_i.The constraint on u_{ij} is $\sum_{i=1}^{c}u_{ij}=1$ and m is the fuzzification coefficient.

The general framework of MAFCM aims to minimize the objective function

$$Q=\sum_{i=1}\sum_{j=1}u_{ij}^{m}\left\|\varphi_{com}(x_j)-\varphi_{com}(o_i)\right\|^2$$

To enhance the Gaussian-kernel-based KFCM-F by adding a local information term in the objective function

$$Q=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}(1-k(x_j,o_i))+\alpha\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}(1-k(\bar{x}_j,o_i))$$

where *xj* is the intensity of pixel *j*. In the new objective function, the additional term is the weighted sum of differences between the filtered intensity *xj* (the local spatial information) and the clustering prototypes. The differences are also measured using the kernel-induced distances. Such kind of enhanced KFCM-based algorithm is denoted as AKFCM (with a standing for additional term).

It is worth pointing out that $k_1$or k_2 in the first variant of MAFCM-K-based image segmentation can be changed to any other Mercer kernel function for the information related to image pixels. This empowers the flexibility to the segmentation algorithm in kernel function selections and combinations. For example, a composite kernel that joins different shaped kernels can be defined as

$$k_{com} = k_1 + \alpha k_2$$

where k_1 is still the Gaussian kernel for pixel intensities

$$k_1(\mathbf{x}_i, \mathbf{x}_j) = \exp(-|x_i - x_j|^2/r^2),$$

k_2 is a polynomial kernel for the spatial information

$$k^2(\mathbf{x}_i, \mathbf{x}_j) = (x_i x_j + d)^2$$

If $k$com = k1 + αk2 is the composite kernel, the minimized objective function of the MAFCM is derived as

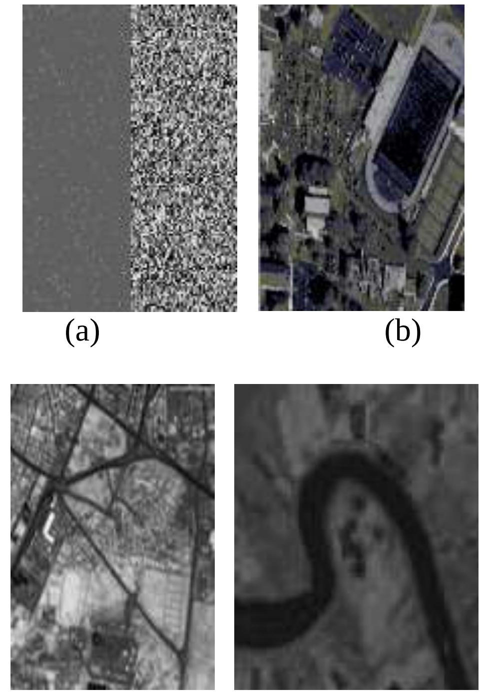
$$Q = \sum_{i=1}\sum_{j=1}^{n} u_{ij}^{m} \left\| \varphi_{com}(x_j) - o_i \right\|^2$$

For example, the input image data x j is set to be xj = [xj , xj, sj] ∈ R3, the same as the third variant of MAFCM, then the composite kernel is designed as

$$k_L = w_1^b k_1 + w_2^b k_2 + w_3^b k_3$$

The MAFCM algorithm evaluates the centroids so as to minimize the influence of outliers. Unlike FCM, it does not attempt fuzzification for elements having membership values above the calculated threshold. This reduces the computational burden compared to FCM, also there is an absence of external user-defined parameters. The removal of this initial trial and error factor makes MAFCM more robust, as well as insensitive to the fluctuations in the incoming data. The elevation and reduction of the membership values to 1 and 0, respectively, results in contrast enhancement in the observability of the incoming data. This helps in focusing on the ambiguous boundary region; thereby gaining in terms of the quality of segmentation.

Figure1: a) Synthetic texture image b) sample satellite image c) low resolution satellite image1 d) low resolution satellite image2



(a) (b)

(c) (d)

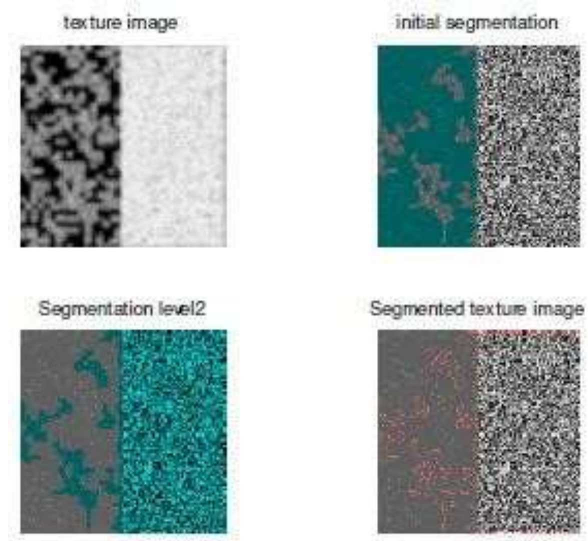
To further improve the performance of segmentation, MAFCM that linearly combines three kernels, i.e., the first two kernels are the kernels for intensities and the local spatial information. To sum up, the merit of MAFCM-based image-segmentation algorithms is the flexibility in selections and combinations of the kernel functions in different shapes and for different pieces of information. After combining the different kernels in the kernel space (building the composite kernel), there is no need to change the computation procedures of MFKCM. This is another advantage to reflect and fuse the image information from multiple heterogeneous or homogeneous sources. MAFCM-based image-segmentation algorithms are inherently better than other KFCM-based image segmentation methods. We can demonstrate the MAFCM's significant flexibility in kernel selections and combinations and the great potential of this flexibility could bring to image segmentation problems. In the MAFCM framework, we can easily fuse the texture information into segmentation algorithms by just adding a kernel designed for the texture information in the composite kernel. As in the satellite image-segmentation and two-texture image-segmentation problems, simply adding a Gaussian kernel function of the texture descriptor in the composite kernel of MAFCM leads to better segmentation results.

4. Experimental Results

In this section, we present the texture based segmentation and MAFCM-based segmentation for synthetic images (texture images). Since the proposed MAFCM-based image segmentation algorithm provides better segmentation results, it is applied for various satellite images. The performance of FCM-type algorithms depends on the initialization, this paper does the initialization and iterations depend upon the input images and chooses the one with the best objective function value. This increases the reliability of comparison results acquired in the simulations. In MAFCM, the different kernels, balances the importance of pixel intensities and the local spatial information. The main goals of an image segmentation algorithm are optimization of segmentation accuracy and its efficiency. Considering accuracy, the proposed method is concentrated on obtaining a robust segmentation for noisy images) and a correct detection of small regions.

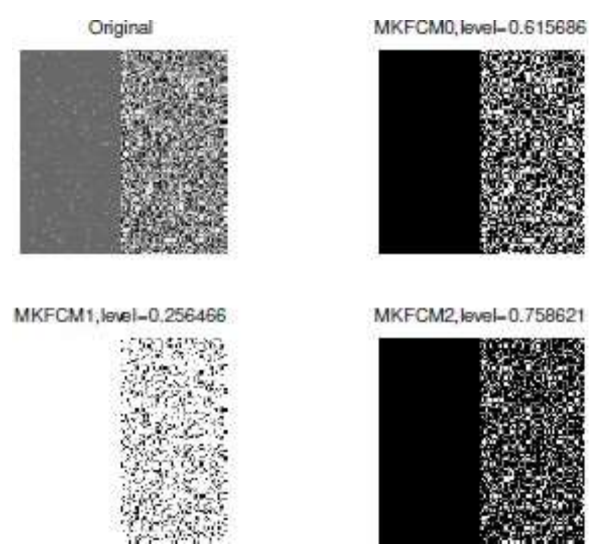
To demonstrate the flexibility and the advantages of MAFCM, a two-texture image is tested in this simulation. Figure.2 shows the segmentation performance of texture segmentation algorithm for synthetic image. The segmented image is as shown in Figure. 2, in which the left half of the image and the right half are of great difference because the left half is coarse and the right half is smooth, i.e., their textures are visibly different. Traditional enhanced KFCM-based algorithms like DKFCM and AKFCM cannot deal with this kind of image very well, because they only consider the local spatial information. While considering the problem in the MAFCM framework, we can simply apply the combined kernel like the Gaussian kernel for the texture information.

Figure 2: Texture based segmentation in synthetic image



In the figure 2, we observed that the texture segmentation yields the segmented image with overlapping with the adjacent pattern. In addition, it requires more number of image processing stages like histogram equalization, image interpolation and edge detection based rough segmentation. Figure.3 shows the segmentation result of the MAFCM for the same texture image. Due to the consideration of the texture information, it has a better result than texture segmentation other FCM based methods.

Figure 3: MAFCM based segmentation in synthetic image



In order to evaluate the performance of the proposed method in detecting small regions, the algorithm was applied on satellite by considering different number of clusters. In these images, the clusters appear with widely varying sizes, and thus, one can evaluate the ability of an algorithm in detecting small regions. As can be seen from these results, the performance of MAFCM and KFCM algorithm provides useful detailed information before defuzzification that can be utilized in algorithms such as the proposed method. Also note that the segmentation result of the proposed method is the best with respect to robustness against noise and preserving the details of the object borders.

Although the proposed method utilizes some processing units that are not used in the KFCM method, its overall elapsed time for the multispectral data sets is less than that of the KFCM method. It is mainly obtained by reduction of spatial redundancy in the image tessellation step of the watershed transform block. Figure.4 and Figure.5 shows the simulation results obtained for a sample satellite image and low resolution satellite image. Figure.4 requires less number of iterations and segmentation has been achieved for less threshold level but the low resolution image in Figure.5 requires more number of iterations and high threshold level compared to the sample satellite image in Figure. 4.

Figure 4: MAFCM based segmentation in sample satellite image

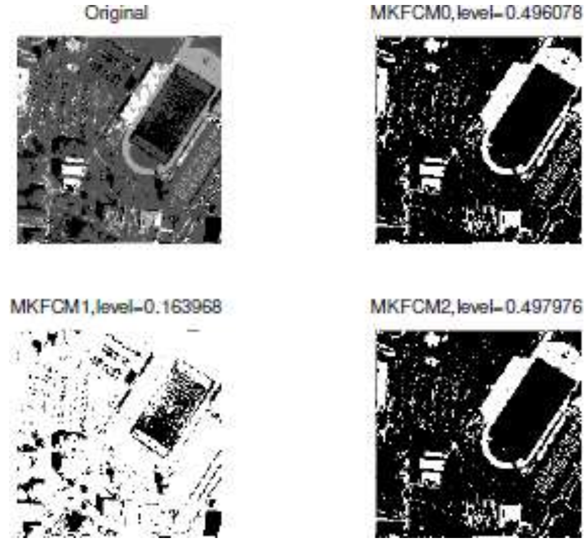


Figure 5: MAFCM based segmentation in low resolution satellite image

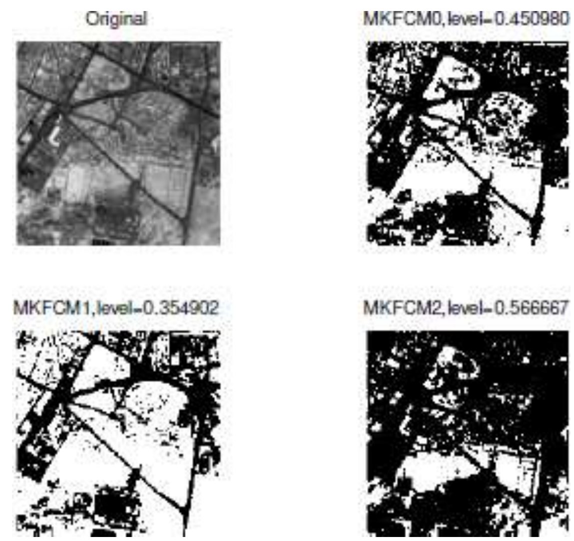


Figure 6: KFCM based segmentation in low resolution satellite image

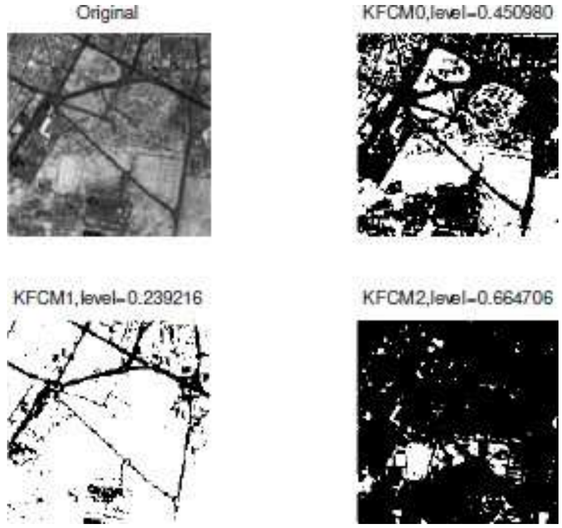
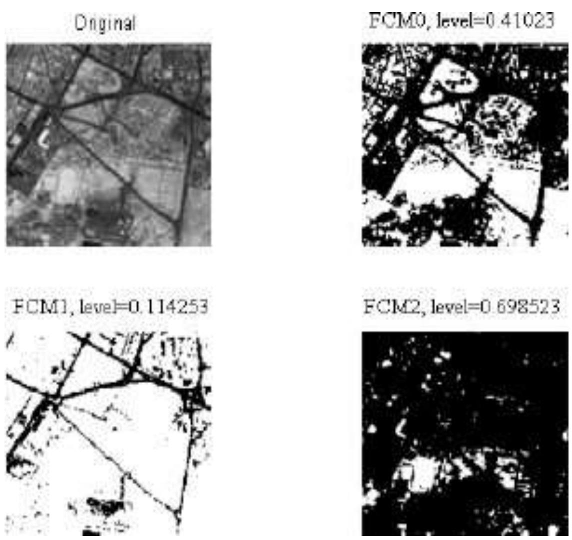


Figure 7: FCM based segmentation in low resolution satellite image



The MAFCM algorithm performs well for normal images and low resolution images. The performance of MAFCM algorithm is compared with the KFCM and FCM algorithm as shown in the Figure.6 and Figure 7.Is to identify the number of iterations and threshold level as shown below tables:

Table 1: Threshold level Comparison

Algorithm	FCM	KFCM	MAFCM
Texture image	0.974	0.854	0.758
Sample satellite image	0.616	0.594	0.498
Low resolution satellite image 1	0.634	0.645	0.567
Low resolution satellite image 1	0.698	0.632	0.582

Table 2: Comparison using number of iterations

Algorithm	FCM	KFCM	MAFCM
Texture image	180	116	95
Sample satellite image	102	75	43
Low resolution satellite image 1	98	78	73
Low resolution satellite image 1	98	76	72

5. Conclusion

Satellite images often require segmentation in the presence of uncertainty, caused due to factors like environmental conditions, poor resolution and poor illumination. The Modified Adaptivefuzzy C-means clustering (MAFCM) methodology for satellite image segmentation has been presented in this paper. The proposed MAFCM algorithm provides us a new flexible methodology for image segmentation problems. That is, different pixel information represented by different kernels is combined in the kernel space to produce a new kernel. It is shown that this algorithm performs better than the kernel fuzzy C-means clustering algorithm. Simulations are performed on the synthetic texture and satellite images to demonstrate the flexibility and advantages of MAFCM-based approaches.

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