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Land cover classification using reformed fuzzy C-means

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Abstract. This paper explains the task of land cover classification using reformed fuzzy C means. Clustering is the assignment of objects into groups called clusters so that objects from the same cluster are more similar to each other than objects from different clusters. The most basic attribute for clustering of an image is its luminance amplitude for a monochrome image and colour components for a colour image. Since there are more than 16 million colours available in any given image and it is difficult to analyse the image on all of its colours, the likely colours are grouped together by clustering techniques. For that purpose reformed fuzzy C means algorithm has been used. The segmented images are compared using image quality metrics. The image quality metrics used are peak signal to noise ratio (PSNR), error image and compression ratio. The time taken for image segmentation is also used as a comparison parameter. The techniques have been applied to classify the land cover.

Keywords. Land cover; FCM; RFCM; clustering; compression ratio; PSNR; kappa coefficient.

1. Introduction

Land cover refers to features of land surface. These can be natural, semi-natural, managed or totally man-made. They are directly observable. The main reason for producing land cover maps is to give us a clear idea of the stock and state of our natural and built resources. A land cover classification, is an essential component in developing a responsible attitude to environmental management. Land cover is distinct from land use despite the two terms often being used interchangeably. Land use is a description of how people *utilize* the land and socio-economic activity–urban and agricultural land uses are two of the most commonly recognised high-level classes of use. At any one point or place, there may be multiple and alternate land uses, the specification of which may have a political dimension. Land cover classifications are essential inputs to environmental and land use planning at local, regional, and national levels. This paper uses segmentation based on unsupervised clustering techniques for classification of land cover.

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Partitioning of an image into several constituent components is called image segmentation. Segmentation is an important part of practically any automated image recognition system, because it is at this moment that one extracts the interesting objects, for further processing such as description or recognition. Segmentation of an image is in practice the classification of each image pixel to one of the image parts. So image segmentation and classification of its pixels into groups are one and the same, the words clustering and segmentation are used alternatively.

Image segmentation has been the subject of considerable research activity over the last three decades. Many unsupervised algorithms have been developed for segmenting gray scale images. In computer vision literature, various methods dealing with segmentation and feature extraction are discussed, which can be broadly grouped into region-based techniques, edge-based techniques, hybrid methods which combine edge and region methods, and so on. However, because of the variety and complexity of images, robust and efficient segmentation algorithm on colour images are still a very challenging task and fully automatic segmentation procedures are far from satisfying in practical situations As colours convey more information than the intensities, this paper explains the task of classifying each pixel in an image into one of a discrete level of colour classes using different fuzzy clustering techniques. Colour image segmentation is done by mapping of a pixel into a point in an n-dimensional feature space, defined by the vector of its feature values. The problem is then reduced to partitioning the feature space into separate clusters, which is a general pattern recognition problem.

The paper is organized as follows. The earlier related works and their limitations are discussed in section 2. In section 3, different clustering techniques and classification method are discussed. In section 4, composite satellite image and colour components of different surface features are dealt with. In section 5, important quality measurement techniques like PSNR, error image are discussed. Evaluation of results and land cover classification are given in section 6. Concluding remarks are given in section 7.

2. Related work

Fuzzy C-means is a method of clustering which allows one data to belong to two or more clusters. This method was developed by Dunn (1973) and improved by Bezdek (1981) and is frequently used in image segmentation and pattern recognition. The main disadvantage of FCM is that the sum of membership values of a data point in all the clusters must be one and so the algorithm has difficulty in handling outlier points (Cox 2005). Frank Klawonn & Annette Keller (1997) have proposed a modified C-means algorithm with changed distance function which is the dot product instead of the conventional Euclidean distance. This method is used for identifying clusters of new shapes. An additional term is injected into the objective function to constrain the behaviour of membership functions with the neighbourhood effect by Lei Jiang & Wenhui Yang (2003). Krishnapuram & Keller (1996) have proposed a fuzzy-possibilistic C-means (FPCM) model and algorithm that generated both membership and typicality values when clustering unlabelled data. FPCM constrains the typicality values so that the sum of over all data points of typicality to a cluster is one. The row sum constraint produces unrealistic typicality values for large data sets. Later they have modified it by a new model called possibilistic-fuzzy C-means (PFCM) model. PFCM produces memberships and possibilities simultaneously, along with the usual point prototypes or cluster centers for each cluster (Pal *et al* 2005). Both FPCM and PFCM require some boot strap method for initialization of weights.

FCM is the most popular fuzzy clustering algorithm. Researchers have used this algorithm for different applications. Problems related to remote sensing data clustering for both supervised and unsupervised classification can be solved by FCM. Wang used supervised FCM to classify the Landsat MSS and TM data with seven land cover classes (Wang 1990). The results were compared with the maximum likelihood classification. The conclusion was that higher classification accuracy could be achieved while using fuzzy classification approach. Foody has evaluated the performance of FCM and fuzzy neuron network for land cover classification from airborne thematic mapper (ATM) data. He studied the effect of different fuzzy parameter (m) values for the same dataset and found that $m = 2.0$ gives most accurate fuzzy classification output for many cases. He concluded that the fuzzy classification technique provides more appropriate results in land cover mapping than hard classification techniques (Foody 1996). Bastin compared FCM, linear mixture modeling and maximum likelihood classifier for unmixing coarse pixels present in aggregated Landsat TM data. In absence of ground truth the original TM data were used as reference map and aggregated the image using mean and cubic filter with different kernel size. The author concluded that FCM gives the best prediction of sub-pixel land cover classes for the aggregated TM image at different scale (Bastin 1997).

Foody & Zhang (1998) used fuzzy C means algorithm for sub-urban land cover mapping from SPOT HRV and Landsat TM data. They found that the classification results could be improved significantly while using fuzzy classification and evaluation approaches (Foody & Zhang 1998). Ibrahim *et al* (2005) compared different fuzzy classification techniques to generate accurate land cover maps in presence of uncertainties. In their study they concluded that possibilistic means gives the highest accuracy in land cover mapping, followed by the FCM technique (Ibrahim *et al* 2005).

3. Fuzzy clustering algorithms and classification method

In real applications very often no sharp boundary between clusters so that fuzzy clustering is often better suited for the data. Membership degrees between zero and one are used in fuzzy clustering instead of crisp assignments of the data to clusters.

The resulting data partition improves data understanding and reveals its internal structure. Partition clustering algorithms divide up a data set into clusters or classes, where similar data objects are assigned to the same cluster whereas dissimilar data objects should belong to different clusters.

Areas of application of fuzzy cluster analysis include data analysis, pattern recognition, and image segmentation. The detection of special geometrical shapes like circles and ellipses can be achieved by so-called shell clustering algorithms.

3.1 *Fuzzy C means*

The most prominent algorithm is the FCM or fuzzy C means algorithm. The fuzzy C means algorithm was proposed as an improvement of the classic hard C-means clustering algorithm. The FCM algorithm receives the data or the sample space, an $n \times m$ matrix where n is the number of data and m is the number of parameters. The number of clusters c, the assumption partition matrix U, the convergence value E all must be given to the algorithm. The assumption partition matrix has c number of rows and n number of columns and contains values from 0 to 1.

The sum of every column has to be 1. The first step is to calculate the cluster centers. This is a matrix v of dimension c rows with m columns. The second step is to calculate the distance matrix D. The distance matrix constitutes the Euclidean distance between every pixel and every cluster center. This is a matrix with c rows and n columns. From the distance matrix the partition matrix U is calculated.

If the difference between the initial partition matrix and the calculated partition matrix is greater than the convergence value then the entire process from calculating the cluster centers to the final partition matrix is repeated. The final partition matrix is taken and is used for reconstructing the image. Let us assume as a fuzzy C-Means Functional,

$$J_m(U, Y) = \sum_{k=1}^{n} \sum_{j=1}^{c} u_{jk}^m E_j(x_k), \tag{1}$$

where, $X = \{x_k | k \in [1,n]\}$ is the training set containing n unlabelled samples, $Y = \{y_j | j \in [1,c]\}$ is the set of centers of clusters, $E_j(x_k)$ is a dissimilarity measure (distance or cost) between the sample x_k and the center y_j of a specific cluster j, $U = [u_{jk}]$ is the $c \times n$ fuzzy c-partition matrix, containing the membership values of all samples in all clusters and $m \in (1, \infty$ is a control parameter of fuzziness.

The clustering problem can be defined as the minimization of J_m with respect to Y, under the *probabilistic constraint*:

$$\sum_{j=1}^{c} (u_{jk}) = 1. \tag{2}$$

The fuzzy C-means (FCM) algorithm consists in the iteration of the following formulas. The cluster centers are calculated by,

$$y_j = \frac{\sum_{k=1}^{n} (u_{jk})^m x_k}{\sum_{k=1}^{n} (u_{jk})^m} \quad \forall j, \tag{3}$$

and the membership values are determined by,

$$u_{jk} = \left(\sum_{l=1}^{c} \left(\frac{E_j(x_k)}{E_l(x_k)} \right)^{2/m-1} \right)^{-1} \quad if\ E_j\ (x_k)\rangle\, 0\ \forall j, k \tag{4}$$

$$1\ if\ E_j(x_k) = 0\ and\ u_{jk} = 0\ \forall l \neq jk,$$

whereas, in the case of the Euclidean space

$$E_j = \left\| x_k - y_j \right\|^2. \tag{5}$$

It is worth noting that if one chooses $m = 1$ the fuzzy C-means functional J_m

Eq. 1 reduces to the expectation of the global error

$$\langle E \rangle = \sum_{k=1}^{n} \sum_{j=1}^{c} u_{jk} E_j(x_k), \tag{6}$$

and the FCM algorithm becomes the classic hard C-means algorithm.

3.2 *Possibilistic fuzzy C means*

In the possibilistic approach to clustering the membership function or the degree of *typicality* of a point in a *fuzzy* set (or cluster) is assumed to be absolute. In other words, the degree of typicality does not depend on the membership values of the same point in other clusters contained in the problem domain. By contrast, many clustering approaches impose a probabilistic constraint, according to which the sum of the membership values of a point in all the clusters must be equal to one. As a consequence, HCM, FCM and many other clustering methods assuming the probabilistic constraint cannot generate membership functions whose values can be interpreted as degrees of *typicality*.

PCM algorithm avoids the assumption of the probabilistic constraint. The PCM is based on the relaxation of the probabilistic constraint in order to interpret in a *possibilistic* sense the membership function or degree of *typicality*. The possibilistic C-means algorithm I is based on a modification of the objective function of FCM. In this case, one must supply the values of some parameters such as the *fuzzifier parameter*, and others regulating the weight of the spread of membership functions. The possibilistic C-means algorithm II is based on modification of the cost function of the HCM instead of the FCM in order to avoid, in this way, the determination of the fuzzifier parameter. The objective function of the PCM-II contains two terms as shown below.

$$J(U, Y) = \sum_{k=1}^{n}\sum_{j=1}^{c} u_{jk} E_j(x_k) + \sum_{j=1}^{c} \rho_j \sum_{k=1}^{n} (u_{jk} \ \ln \ u_{jk} - u_{jk}). \tag{7}$$

The first one is the objective function of the HCM, while the second is a regularizing term, forcing the values u_{jk} to be greatest as possible, in order that points with a high degree of typicality with respect to a cluster may have high u_{jk} values, and points not very representative may have low u_{jk} values in all clusters. In the above equation $E_j(x_k) = |x_k - y_j|^2$ is the square of the Euclidean distance, and the parameter P_j depends on the distribution of point in the j^{th} cluster.

$$y_j = \frac{\sum_{k=1}^{n} (u_{jk})\ x_k}{\sum_{k=1}^{n} (u_{jk})} \quad \forall j \tag{8}$$

$$u_{jk} = \exp\left\{-\frac{E_j(x_k)}{\rho_j}\right\} \quad \forall j, k. \tag{9}$$

This theorem provides the conditions needed in order to minimize the cost function. The above two equations can be interpreted as formulas for recalculating the membership functions and the cluster centers. A bootstrap clustering algorithm is anyway needed before starting PCM in order to obtain an initial distribution of prototypes in the feature space and to estimate some parameters used in the algorithm. By considering an FCM bootstrap for the PCM, the following definition of P_j can be used.

$$\rho_j = K\frac{\sum_{k=1}^{n} (u_{jk})^m E_j(x_k)}{\sum_{k=1}^{n} (u_{jk})^m}, \tag{10}$$

where, m is the *fuzzifier* parameter used by the FCM, and K is a proportional parameter. This definition makes ρ_j proportional to the mean value of the intracluster distance, and critically depends on the choice of K.

3.3 *Reformed fuzzy C means*

For reformed fuzzy C means a neighbourhood influence parameter γ at each pixel is calculated. It is determined by convolving original gray scale image with a template of 3×3 matrix of ones. The probabilistic constraint is removed by equating sum of membership function in a cluster to n.

$$\sum_{j=1}^{c} (u_{jk}) = n. \tag{11}$$

The distance measure is modified by the neighbourhood influence parameter γ. The distance measure is

$$E_j = \left\| x_k - y_j \right\|^2 e^{-\gamma k}. \tag{12}$$

The membership values are determined by,

$$u_{jk} = \left\{ \begin{array}{c} n * \left(\sum_{l=1}^{c} \left(Z_j \left(x_k \right) E_j \left(x_k \right) \right)^{2/m-1} \right)^{-1} \quad if \ E_j \ (x_k) \rangle \, 0 \ \forall j, k \\ 1 \ if \ E_j(x_k) = 0 \quad and \quad u_{jk} = 0 \ \forall l \neq jk, \end{array} \right\} \tag{13}$$

where Z_j is,

$$z_j = \sum_{k=1}^{c} \frac{1}{E_k}. \tag{14}$$

3.4 *Classification method*

The satellite image pixels are classified by maximum membership method. The partition matrix gives the extent to which each pixel belongs to different clusters. From the partition matrix, the optimal cluster to which the pixel maximum belongs to is selected. For each pixel, the row number of largest element in each column of the partition matrix is found and the pixel is assigned the cluster center value, corresponding to that row. In this way, each pixel is assigned, a cluster center value determined by the clustering algorithm.

4. Geocover (composite landsat 7 satellite) image and surface features

Earth observation satellites are satellites specifically designed to observe Earth from orbit. These satellites are used for environmental monitoring, meteorology, map making, etc. Satellites observe the Earth with different filters or bands.

The Landsat satellites have been launched to observe the Earth, and the data collected have been used to study the Earth's environment, resources, and natural and man-made changes on the Earth's surface. Landsat 7 which has been launched in April 15, 1999 carries an enhanced thematic mapper plus (https://zulu.ssc.nasa.gov/mrsid/tutorial/Landsat%20Tutorial-V1.html). The spectral sensitivity of Landsat 7 bands are listed in table 1.

Table 1. Spectral sensitivity of landsat 7 bands.

Band	Spectral sensitivity
1	.45–.52 μm blue
2	.53–.61 μm green
3	.63–.69 μm red
4	.75–.9 μm Near IR
5	1.55–1.75 μm Short Wave IR
6	10.4–12.5 μm Thermal IR
7	2.1–2.35 μm Short Wave IR
8	.52–.9 μm Panchromatic

The Band 2: 0.52–0.60 μm (green) corresponds to the green reflectance of healthy vegetation and is spanning the region between the blue and red chlorophyll absorption bands and Band 3: 0.63–0.69 μm (red) chlorophyll absorption band of healthy green vegetation is one of the most important bands for vegetation discrimination and Band 4: 0.76–0.90 μm (near infrared) band is especially responsive to the amount of vegetation biomass present in a scene. It is useful for identification of vegetation types, and emphasizes soil–crop and land–water contrasts. A false colour composite was compiled using bands 2, 3 and 4. This composite image was used in our work for this band combination. Based on the technical expertise the surface features were identified from the tonal variations that are given in table 2.

5. Quality measures used for image segmentation and land cover classification

The quality measures used for evaluating the image segmentation are peak signal to noise ratio, compression ratio and execution time. Kappa coefficient is used for evaluating the land cover classification.

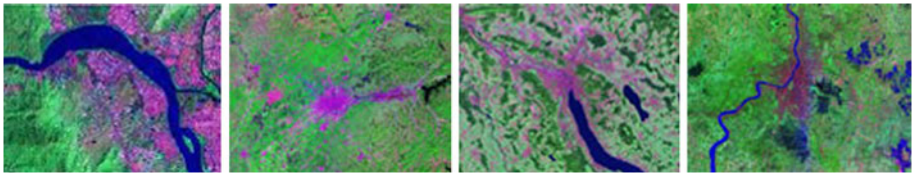
5.1 *Peak signal to noise ratio*

Signal-to-noise (SNR) measures are estimates of the quality of a reconstructed image compared with an original image. The basic idea is to compute a single number that reflects the quality of the reconstructed image. Reconstructed images with higher metrics are judged better. In fact, traditional SNR measures do not equate with human subjective perception. Several research groups are working on perceptual measures, but for now signal-to-noise measures are used because they are easier to compute. Also, to be noted that higher measures do not always mean better quality.

The actual metric that is computed in this work is the peak signal-to-reconstructed image measure, which is called PSNR. Assume a source image f(i,j) is given that contains M by N pixels and a reconstructed image F(i,j) where F is reconstructed by decoding the encoded version

Table 2. Surface features and colour components.

Surface feature	Colour component
Forests and Vegetation	Shades of green
Water	Black to dark blue
Urban areas	Lavender
Bare soil	Magenta, lavender, or pale pink



Mumbai, India Shenyang, China Zurich, Switzerland Kolkatta, India

Figure 1. Landcover images.

of f(i,j). Error metrics are computed on the luminance signal only so the pixel values f(i,j) range between black (0) and white (255).

First the mean absolute error (MAE) of the reconstructed image is computed as follows

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|F(i,j) - f(i,j)|. \tag{15}$$

The summation is over all pixels. PSNR in decibels (dB) is computed by using

$$\mathrm{PSNR} = 20\ \log_{10}\left(255^2/\mathrm{MAE}\right).$$

Typical PSNR values range between 20 and 40. They are usually reported to two decimal points (e.g., 25.47). The actual value is not meaningful, but the comparison between two values for different reconstructed images gives one measure of quality. The MPEG committee used an informal threshold of 0.5 dB PSNR to decide whether to incorporate a coding optimization because they believed that an improvement of that magnitude would be visible. Some definitions of PSNR use 255/RMAE rather than 255^2/MAE. Either formulation will work because we are interested in the relative comparison, not the absolute values. In our assignments we used the definition given above.

5.2 *Error image*

The other important technique for displaying errors is to construct an error image, which shows the pixel-by-pixel errors. The simplest computation of this image is to create an image by taking the difference between the reconstructed and original pixels. These images are hard to see because zero difference is black and most errors are small numbers, which are shades of black. The typical construction of the error image multiples the difference by a constant to increase the visible difference and translates the entire image to a gray level. The computation is

$$E(i,j) = 2\,|F(i,j) - f(i,j)| + 128. \tag{16}$$

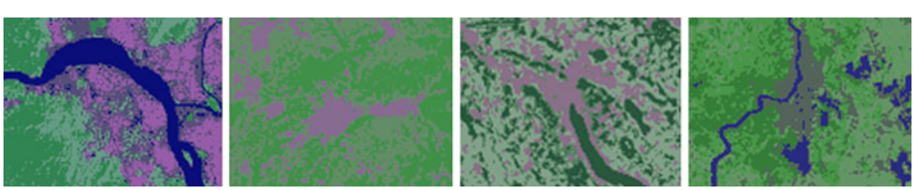


Figure 2. Classified by FCM.

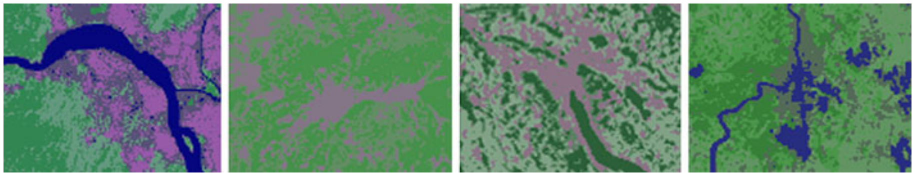


Figure 3. Classified by PFCM.

The constant 2 or the translation 128 can be adjusted to change the image. Some people use white (255) to signify no error and difference from white as an error which means that darker pixels are bigger errors.

5.3 *Compression ratio*

Data compression is the process of reducing the data required to represent information. It removes redundant and non essential data. Image segmentation can be thought of as a form of data compression, where a large number of data are converted into a small number of representative prototypes or clusters. Compression ratio is the ratio of number of bits represented by n_1 required to represent the uncompressed original image and that of the image compressed n_2.

$$C_R = \frac{n_1}{n_2}. \tag{17}$$

If the compression ratio is more then the data required to represent the image is less. But it results in loss of data.

5.4 *Kappa coefficient*

When two binary variables are the measure of the same thing, Cohen's Kappa or Kappa Coefficient can be used as a measure of agreement between the two variables. If one variable is assumed to be the correct measure then Kappa coefficient will be the measure of correctness of the second one.

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)},$$

where $\Pr(a)$ is the relative observed agreement among variables, and $\Pr(e)$ is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each variable randomly saying each category. If the variables are in complete agreement then $K = 1$. If there is no agreement among the variables then $K \leq 0$.

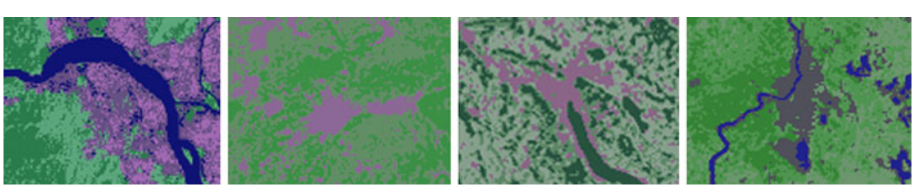


Figure 4. Classified by RFCM.

Table 3. Evaluation of segmentation.

Image	Size in pixels	No. of clusters	Method	Cluster centers			PSNR	Execution time	Compression ratio
Mumbai, India	163 × 126	5	FCM	5.54852	6.995534	124.6308	32.4526	151.563	9.587489
				99.25055	153.4096	126.8716			
				86.67344	81.11455	118.8965			
				49.61065	134.2704	81.54963			
				149.9632	89.56819	167.9029			
			PFCM	10.03087	14.0207	121.1471	32.7889	1.829	9.607297
				101.2646	155.3668	132.4036			
				85.26881	79.12473	119.648			
				48.69576	133.232	82.1102			
				151.4832	93.07632	168.678			
			RFCM	14.56414	18.69687	116.2454	32.8520	104.469	9.914156
				92.30112	166.1601	125.0425			
				102.9769	80.06269	132.1856			
				43.01532	124.1328	77.32972			
				162.4049	105.648	179.0658			
Shenyang, China	125 × 94	3	FCM	131.8987	118.0463	134.9037	33.4913	8.297	15.24654
				98.97786	141.6405	100.7609			
				70.16353	145.0685	75.05509			
			PFCM	135.3381	106.6113	144.8439	34.2036	0.031	15.42163
				99.38578	140.8864	102.7347			
				63.90597	144.2565	73.56479			
			RFCM	140.4891	100.8813	151.7446	34.2995	10.812	15.89807
				99.74692	141.7331	103.078			
				60.3496	143.9429	70.94353			

Zurich, Switzerland	125 × 94	4	FCM	129.2441	161.9289	135.2692	34.9313	21.672	12
				138.1519	115.4862	132.9529			
				85.85966	129.8844	94.97673			
				44.03998	96.26197	57.05611			
			PFCM	129.2251	161.275	136.8044	35.4844	0.032	12
				138.0266	111.7683	135.8289			
				85.49063	127.5205	96.36138			
				41.42755	87.5087	61.55836			
			RFCM	92.05618	135.2578	101.8366	35.5132	40.672	12
				135.4813	158.9497	140.9448			
				138.4137	100.656	135.5725			
				39.64052	83.19005	64.42115			
Kolkatta, India	125 × 94	5	FCM	74.46361	149.6831	74.2034	35.7983	47	9.650924
				83.1478	106.8998	87.03083			
				38.67138	46.44336	127.3815			
				55.73424	128.2477	57.6703			
				98.46141	148.558	99.14356			
			PFCM	73.47007	150.4768	74.81313	36.6674	0.047	9.849808
				83.78663	99.76427	89.66674			
				39.55282	44.11511	127.7938			
				54.45434	124.9829	56.79731			
				100.2751	149.3944	102.4818			
			RFCM	79.5971	148.4866	81.69702	36.7379	55.453	10.67212
				79.21054	80.42191	89.30385			
				31.65943	34.49818	141.8317			
				52.72183	131.875	54.00553			
				108.2057	149.5642	109.9213			

6. Evaluation of image segmentation and land cover classification

Four test images of different sizes are used for evaluating the results of the proposed method. They are shown in figure 1. They are classified using the fuzzy clustering method. The results of classification using FCM is shown in figure 2. Figure 3 shows the classification by PFCM. The land cover classification by RFCM is shown in figure 4.

The evaluation of segmentation by FCM, PFCM and RFCM for the four test images are given in table 3. In the original image pixels are represented by 8 bits. For the segmented image Huffman coding is considered for the calculation of compression ratio.

From the table it can be seen that segmentation by RFCM gives better PSNR for all images. Though the execution time for PFCM is lesser it has to be taken into account that it requires a bootstrap method for initializing its cluster centers and partition matrix.

The execution time taken by RFCM is slightly higher than the FCM. This is expected because of the modification of calculation of partition matrix and the calculation of neighbourhood influence parameter γ. For the same initial values and termination criterion, i.e., the convergence value of partition matrix, the cluster centers are different for the three algorithms.

The evaluation of classification by FCM, PFCM and RFCM for the four test images are given in table 4. For the calculation of Kappa factor 10 samples of different surface features are considered. For determining Kappa Coefficient for one feature, that particular feature samples are taken as 1 and other feature samples are taken as 0.

For the Mumbai image, Kappa coefficient of RFCM is high for crops and urban area. PFCM's Kappa coefficient is lowest for urban area. The Forest, wetland vegetation, water samples are correctly classified by all three algorithms. The Kappa coefficient of Sheyang image is same for all three algorithms. The wetland vegetation samples of Zurich image is correctly classified by RFCM whereas the other two algorithms resulted in poor classification. For the Kolkatta image, RFCM results in highest Kappa coefficient for all surface features.

Out of the three methods tested RFCM is found to be good on the basis of image reproduction because of increased PSNR, image compression due to the increased compression ratio as well as accurate classification due to highest Kappa coefficient of all surface features.

Table 4. Evaluation of land cover classification.

Image	No. of clusters	Method	Kappa coefficient of different surface features					
			Urban area	Bare soil	Forest	Wetland vegetation	Crops	Water
Mumbai, India	5	FCM	0.8	__	1.0	1.0	0.8	1.0
		PFCM	0.2	__	1.0	1.0	0.8	1.0
		RFCM	1.0	__	1.0	1.0	1.0	1.0
Shenyang, China	3	FCM	0.8	__	0.6	1.0	__	__
		PFCM	0.8	__	0.6	1.0	__	__
		RFCM	0.8	__	0.6	1.0	__	__
Zurich, Switzerland	4	FCM	__	1.0	0.8	0.8	0.8	__
		PFCM	__	1.0	0.8	0.8	0.8	__
		RFCM	__	1.0	0.8	1.0	0.8	__
Kolkatta, India	5	FCM	0.25	1.0	0.8	1.0	__	0.8
		PFCM	0.25	1.0	0.6	1.0	__	0.8
		RFCM	0.83	1.0	0.8	1.0	__	1.0

7. Conclusion

A new reformed fuzzy C means technique has been proposed for land cover classification. The satellite image segmentation and land cover classification by RFCM are compared with that of FCM and PFCM on the quality measures PSNR, compression ratio, execution time and Kappa coefficient. From the quality measures it can be seen that RFCM is better than the other fuzzy clustering techniques. The following points are worth stressing.

(i) The image segmentation by RFCM gives best PSNR. Hence, it is well-suited for image reproduction.
(ii) The compression ratio obtained by RFCM is the Highest. So, it is quite useful for data compression.
(iii) The convergence time of the PFCM is the lowest. But it requires a bootstrap method for cluster centers and partition matrix initialization.
(iv) The Kappa coefficient for all surface features is highest for RFCM. It is very useful for land cover classification.

The program developed has been tested with various pictures and the results were proven to be fruitful. The program has also been tested for its consistency and its reliability. This work is useful for land cover mapping. Land cover maps are essential inputs to environmental and land use planning at local, regional, and national levels. They are being used directly in resource inventories like woodland census, state of the environment reporting like establishing the distribution, extent and quality of key habitats. They also act as input to the development and monitoring of a range of land use and conservation policies.

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