

Building Detection Using a Combined Fuzzy C-Mean and Morphological Filtering from Landsat-8 Satellite Image

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Abstract

Automated building detection from remote sensing has inspired many researchers due to the versatility of it in the creation and updation of Land Information Systems, Geographical Information systems by minimizing the manual effort involved in collecting such large scale data. Considering the free availability, regardless of its coarser spatial resolution, better pattern recognition techniques can come in handy in such cases with freely available satellite images such as Landsat-8. Building detection using low resolution satellite images is a challenging task due to effects such as point Spread Function (PSF), mixed pixels, and vague determination of the building boundaries. Hence precise determination of the boundaries requires robust and novel mechanisms. Because of the information in a pixel of a coarser resolution satellite data within the instantaneous field of view of the sensor is a mixture of different classes and the individual components can be computed using soft classification techniques. The aim of this work is to extract buildings by using Fuzzy C-Mean clustering and morphological filtering. Fuzzy C-Mean clustering is fulfilled by using Brovey pan sharpened image. This image is an input for the Fuzzy C-Mean clustering for image classification. Then rectilinear buildings are extracted using morphological filtering methods. Several experiments were carried out to understand the best pan sharpened technique through this study and effect of different parameters based on Fuzzy C-Mean clustering and morphological filtering. For the purpose of analysis the performance of morphological operation, classification was done for the same study area using Maximum Likelihood (MLC) and Support Vector Machine (SVM) classifiers. The results of different classification techniques were examined by using Regression analysis on the Morphological operated results independently. The results suggest that proposed Fuzzy C Mean classification can improve the building detection by identifying sharp boundaries between land cover classes for remotely sensed data. The results are encouraging with certain improvements enforced.

Key words: Coarser resolution, mixed pixels, point spread function effect, Brovey pansharpened.

1. Introduction

Most of the main Geographic phenomena exist around us can be categorized as natural and manmade. When considering the man-made features buildings play a important role because it is an important class in land cover classification. However collection of this information from remotely sensed data is not an easy task. For that conventional methods such as interpretation of aerial photos can be applied

but they are time consuming, labor consuming and expensive, one of the approaches that have been presented for collecting timely accurate information from earth surface is through satellite images. Unfortunately, most of high resolution satellite images are difficult to obtain by the general researchers, planners, etc. because of their high cost. Thus, it is necessary to develop methods for fast acquisition of up to date urban features such as buildings from freely available low resolution satellite images.

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Figure 1. Katunayake airport, Sri Lanka (source Google Earth)

Building detection from low resolution satellite images has been an important topic in computer vision. But it's still a challenge to isolate the desired objects from the background pixels because these are affected by other features such as vegetation and soil, badly in low resolution satellite images. In remote sensing it assume information contain in each pixel originate directly from within its footprint. But in an actual remote sensing substantial portion of the spectral signal of each pixel coming from the surrounding areas (point spread function effect) (Huang *et al.*, 2002). The other fact is that there are no sharp boundaries between the geographical features. That mean boundary between different objects is fuzzy and assignment of the pixel to a class is uncertain. Generally majority of pixels in coarser spatial resolution satellite images are mixed and recognition of each feature or class becomes more and more difficult, due to the identification of the class and its relative proportion in the mix. Since the manual approaches for building extraction is very time consuming semi-automated methods has been proposed to improve the processing speed. Most of object detection from satellite images are based on the supervised classification techniques. These techniques require training data. This study is carried out in order to develop a method for the acquisition of buildings through the coarser resolution satellite images and adapted a new semi-automated building extraction system applied on low resolution satellite imagery based on Fuzzy C Mean clustering and morphological filtering.

2. Study Area

The study area is the Katunayake area of Sri Lanka. Katunayake International Airport is located in a suburb of Negombo, 22 miles (35 km) north of Colombo. The geographical coordinates of the area are 79°53'2.65"E, 7°10'30.26"N. This area consists of a different land use classes, including built up areas, homestead, coconut, abandoned paddy, water and etc. It can be seen that small buildings are mainly scattered and only few large buildings compact among them. Building detection, which are

approximately more than 15m in width was the main aim of this study. The rest of the buildings in the study area which are very small and close to the each other cannot be recognized even in fused pan sharpened image or even by visual interpretation, so they were not considered in this study. This area contains mixed pixels due to the coarser spatial resolution and PSF.

3. Data

Landsat-8 data with OLI (Operational Land Imager) scanner was used in this study. Bands 1 to 9 were taken as the input for the study. The first 7 bands and band 9 of multispectral data have 30m resolution. Band 8 which is the panchromatic band has spatial resolution of 15m. The digital values of the image were recorded in unsigned 8 bit values. The image was acquired over Katunayake area on 1st January 2015.

Raw Landsat data provide in GeoTIFF format was imported through ENVI 4.8 software and Brovey pan sharpening was done. The Brovey Transformation fusion technique was applied because compared with the other methods Brovey sharpening gives the best performance for this study due to this technique is optimum in high reflectance areas such as urban areas (Nikolakopoulos, 2008).



Figure 2. Pseudo color image from Landsat 8 sensor acquired on 1st January 2015

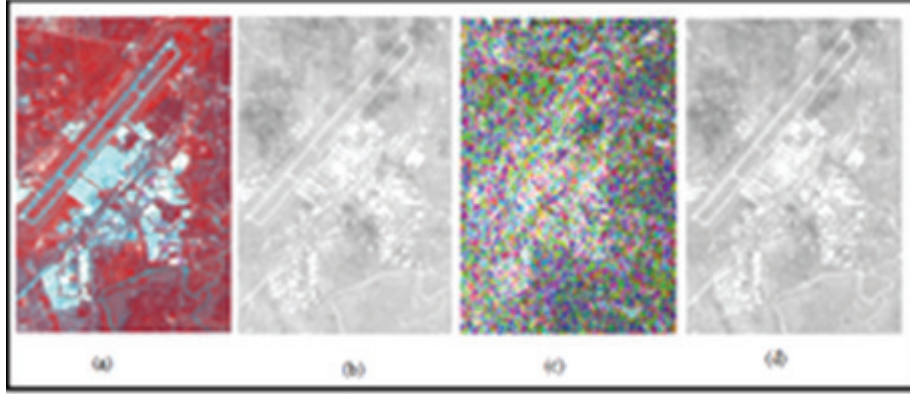


Figure 3. Different fusion techniques using ENVI 4.8 software (a) Brovey (b) Gram Schmidt spectral sharpening (c) HSV (d) PC

4. Methodology

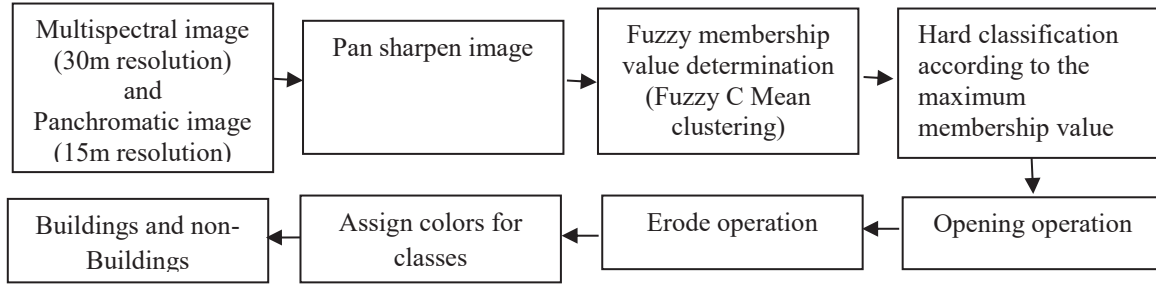


Figure 4. Methodology adopted

5. Fuzzy C-Mean Clustering

Clustering involves the dividing the data points into homogeneous classes so that data points in the same class are similar as possible and data points in the different classes are dissimilar as possible. Many clustering algorithms have been introduced in the literature. Since clusters can formally be seen as subsets of the data set, one possible classification of clustering methods can be according to whether the subsets are fuzzy or crisp (hard). In general, the performance of fuzzy clustering methods is superior to that of the corresponding hard versions, and they are less likely to stick in a local minima (Bezdek, 1981).

In 1965 by Zadeh (Zadeh, 1965) introduced the natural way of dealing with problems in the absence of a sharply defined criteria. The key to Zadeh's idea is to represent the similarity of a point to a cluster with a function (membership function) whose values (memberships) are between zero and one. These indicate the strength of the association between that data element and a particular cluster. Most fuzzy clustering algorithms are based on the objective function, so optimal classification is achieved by minimizing the objective function. Each sample will have a memberships close to unity signify a high degree of similarity between sample and cluster while memberships close to zero imply little similarity between the sample and that cluster

Among the fuzzy clustering methods, Fuzzy C Means (FCM) Algorithm, initially proposed by Dunn 1973 (Dunn, 1973) and eventually modified by Bezdek 1981 (Bezdek, 1981) is the most popular method. Fuzzy C Mean clustering introduced a membership of each sample point in all clusters by a membership function which ranges between zero and one. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of the cluster. The sum of the memberships for each sample point must be unity. The constraint on membership used in FCM is meant to avoid the trivial solution of all membership probabilities being equal to zero (Tso and Mather, 2001). Fuzzy C-mean clustering algorithm can be summarized as follows.

Let $X = \{x_1, x_2, x_3, \dots, x_n\}$ be a set of given dataset, where each data point $x_k (k=1,2,3,\dots,n)$ is a vector. U_{cn} is a set of real matrices and c be an integer, $2 \leq c < n$. then the fuzzy C-mean partition space for X is,

$$M_{fcn} = \{U \in U_{cn} : U_{ik} \in [0,1] \quad \sum_{i=1}^c \mu_{ik} = 1 \quad \forall k \quad \text{where; } 0 \leq \mu_{ik} \leq 1 \quad \forall i, k\} \quad (1)$$

μ_{ik} of the membership of k^{th} data point in the i^{th} cluster, $i = \{1,2,3,\dots,c\}$

The algorithm starts with randomly selecting centers and then in every iteration, determines the Fuzzy membership of each pixel, until there is no change in the cluster centers. In addition, once the cluster centers are established, each pixel is assigned to the group with which it has the highest membership value. It is based on minimization or iterative optimization of the following objective function under the fuzzy constraints defined in (1).

$$J_m = \sum_{k=1}^n \sum_{i=1}^c \mu_{ik}^m d^2(x_k v_i) \quad (2)$$

Where;

$$\mu_{ik} = \left[\sum_{j=1}^c \left[\frac{d(x_k, v_j)}{d(x_k, v_i)} \right]^{\frac{2}{m-1}} \right]^{-1} \quad (3)$$

$$v_i = \frac{\sum_{k=1}^n \mu_{ik}^m x_k}{\sum_{k=1}^n \mu_{ik}^m} \quad (4)$$

The algorithm given in equation (1) is a least squares function, where the parameter n is the number of data sets and c is the number of classes (partitions) into which one is trying to classify the data sets. $d^2(x_k v_i)$ is the Euclidean distance, v_i is center vector of i^{th} cluster and x_k is vector of k^{th} pixel. The process stops when $|\mu^{(t+1)} - \mu^t| \leq \varepsilon$ or a predefined number of iteration is reached, ε is a termination criterion, small positive constant between 0 and 1.

6. Morphological Filtering

Morphological operations are excellent mathematical tools for filtering images. Object detection may result with some noises, the correct detecting of such object play a major role for later recognition steps, the interior noise of the object must be removed and thus Morphological operations play a key role in such applications (Rani, Bansal and Kaur, 2014). Also morphological operation provides shape and boundary description of objects within an image. Morphological operations are spatial dependent and not on spectral information. They are used in pre or post processing (filtering, thinning, and pruning) or for getting a representation or description of the shape of objects/regions (boundaries, skeletons convex hulls) (Kaur, n.d.). The term “morphological image processing” describes a range of non-linear image processing techniques that deal with the shape of features in an image. Morphology operation takes two inputs, the first input is image to be process. It can be binary images (black & white images – Images with only 2 colors: black and white) or grey scale images. In this study greyscale image (resultant image of fuzzy classified image) was used as the input. The second input is structuring element. It is typically smaller than input image. Structuring element is used to modify the input image. So determine the optimum size and the shape of the structuring element is very important and

these parameters were determined manually in this study. The basic concept of morphological operation is “fit and hit”. Morphological operations differ in how they carry out the comparison. Some test whether the structuring element ‘fits’ within the neighborhood; others test whether it ‘hits’ the neighborhood. However Morphological operations transform the image. The two principal morphological operations are dilation and erosion and other morphology operators are often derived from their combination. Both dilation and erosion are produced by the interaction of a structuring element s on the input image f . Dilation of image ‘ f ’ by structuring element ‘ s ’ is given by ‘ $f \oplus s$ ’

$$f \oplus s = \begin{cases} 1; & \text{if 's' hits 'f'} \\ 0; & \text{otherwise} \end{cases} \quad (5)$$

Erosion of image ‘ f ’ by structuring element ‘ s ’ is ‘ $f \ominus s$ ’

$$f \ominus s = \begin{cases} 1; & \text{if s fits f} \\ 0; & \text{otherwise} \end{cases} \quad (6)$$

Before extract the buildings from fuzzy classified image morphological filtering also performed. The aim of the filtering is to remove the objects whose size is lower than the minimum size of the buildings in fuzzy classified image. These objects are considered as the noisy data which is disturbed to building detection. Morphological opening and erode filtering were used to detect buildings respectively. Morphological opening defined as a combination of erosion and dilatation. The opening of image f by structuring element ‘ s ’, denoted ‘ $f \circ s$ ’ is simply the erosion followed by dilation with the same structural element;

$$f \circ s = (f \ominus s) \oplus s \quad (7)$$

7. Results and Discussion

Vegetation surface strongly absorbs radiation in the red and blue wavelength, but reflects green wavelengths. Because of that vegetation surface can measure and monitoring using the Near-Infrared reflectance. This study also verified that general theory, that the Near Infrared band is suitable for vegetation extraction, but not for the man-made feature extraction such as buildings. This study further tells Red and Blue bands are suitable for man-made feature extraction. Visual comparisons of results show clearly soil is not appearing in red band in contrast, they were excluded in the blue band. Building detection result using blue band is in little information loss compared to the red band. The advantage of the blue band for building detection is clearly shown in this comparison. It can be a result of less atmospheric scattering and absorption (or less point spread function) effect in the blue band. The difference between the airport track - building could not be detected completely

using the proposed method due to low spatial resolution of the satellite image, distinct land cover classes may produce similar spectral responses turning more difficult their discrimination. So airport track whose gray value lies in the same spectrum of building roof were committed to the building class in both blue band and red band images. Many

relatively small buildings are distributed over a large part of the scene with sometimes very small gaps between them. Most buildings have been segmented into small fragments and most of them are combined together. In results most of the buildings are merged into a few large building segments which make a meaningful interpretation of the correctness

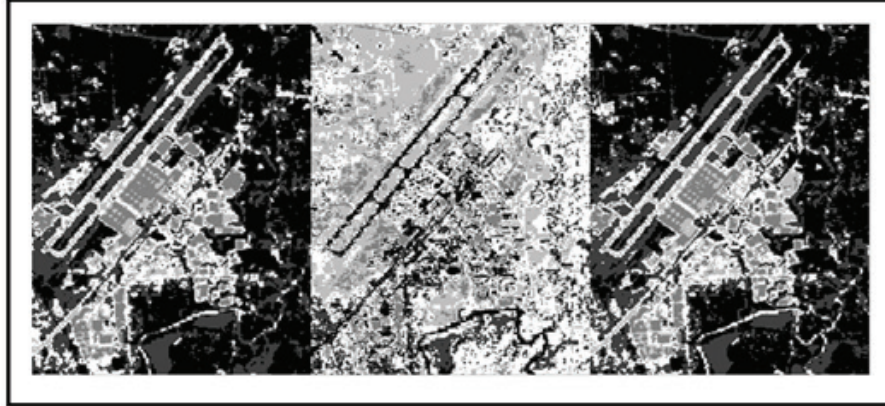


Figure 5. Result of Fuzzy C Mean classifier for Red, NIR and Blue band respectively (Two dimensional matrix). The area was divided into 5 homogeneous classes with $m=2$, minimum amount of improvement= $1e-5$ and the number of iteration=500

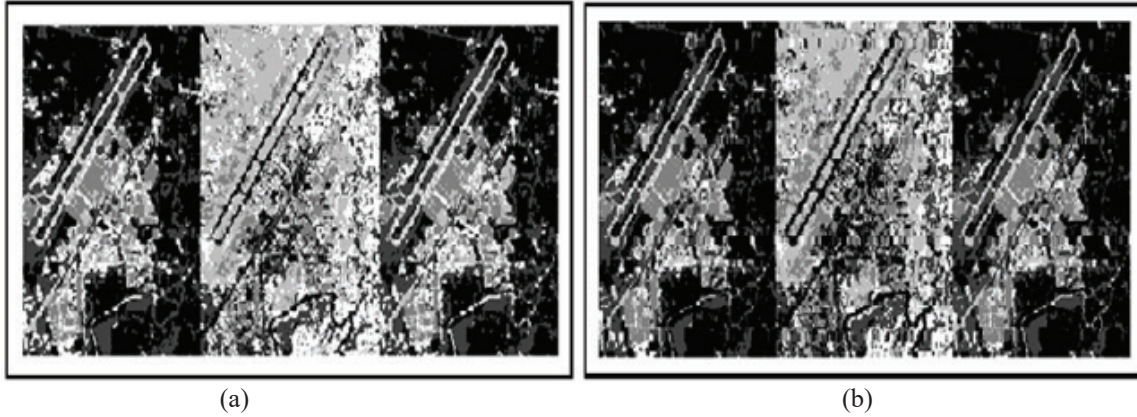


Figure 6. (a) Morphological opening operation and (b) erosion operation respectively for the Fuzzy C Mean classified image using 2×2 structuring element.

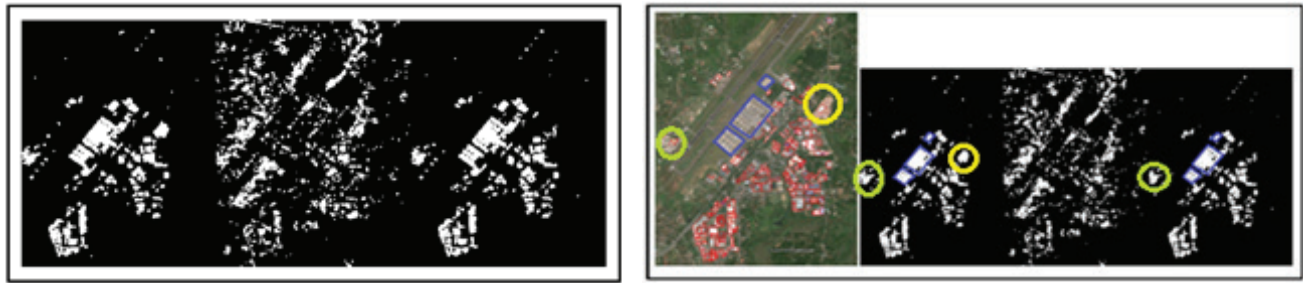
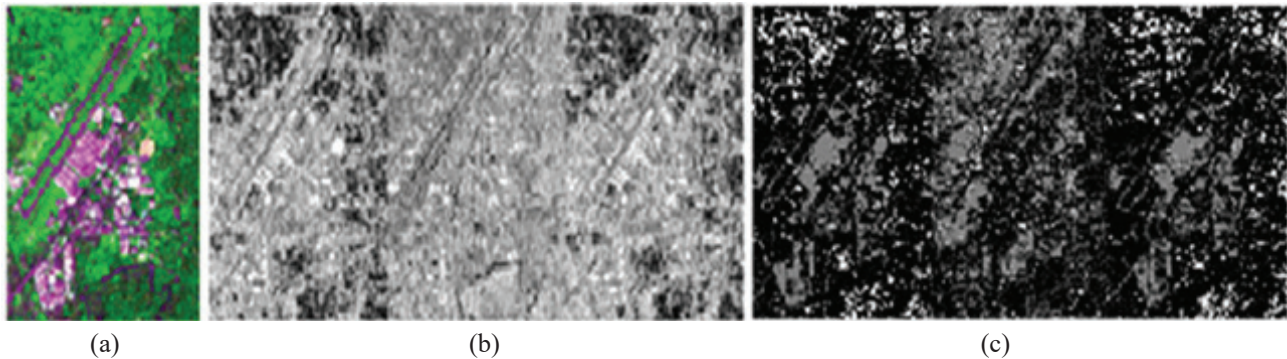


Figure 7. (a) Extracted buildings for Red, NIR and Blue band respectively. (b) The area marked in yellow circle represent the Soil patch misclassified as building in Red band, The areas marked in blue rectangles show an airport track that is misclassified and the area marked in light green represent the Other detection, which misclassified as buildings.

Table 1. Correlation coefficient for images considering the different m values reference to m=2

Fuzzy index	Correlation coefficient of fuzzy component (m) with m=2
m=3	0.9118
m=4	0.8455
m=5	0.7686

Figure 8. (a) Gaussian noise added image, (b) Fuzzy C Mean classification for noisy image and (c) Morphological opening and erode operations for fuzzy classified image using 2×2 structuring imageFigure 9. Fuzzy C Mean classification (m=2, number of iteration=500 and minimum amount of improvement= $1e-5$) for two classes

impossible even in the fused image.

FCM is an iterative method that based on the minimizing an objective function according to the probabilistic constraint that the summation of the membership of each data point should equal to one. Because of that noises also added to the closest cluster center by considering noises are same as data points. However to get a more proper result noises should be assigned to another cluster that the membership value is either zero or very low. One of the major drawbacks in FCM algorithm is its noise sensitivity. But this short come of conventional FCM algorithm can overcome by post processing the clustering result obtained using FCM

algorithm by imposing the spatial information. Combined FCM and morphological filtering gives a better result. This was tested by adding the Gaussian noise to the image. Further the amount of removing noises depends on the size of the structure element.

Another shortcoming in Fuzzy C-mean clustering is difficult to selecting the appropriate parameters to get an optimum result. One of the important parameters is fuzziness index 'm' which influences the performance of the FCM algorithm when clusters in the data set have different densities. An inappropriate value of 'm' leads to unsatisfactory results. The effect of different fuzzy parameter (m) values was

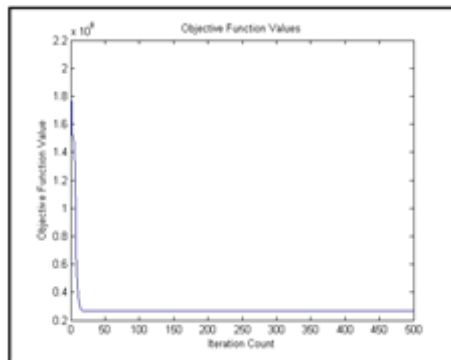


Figure 10. Progress of the clustering plot with the minimization of the objective function

studying for the same dataset. It is noted to get the best result m should be in the range 2-7 and found that $m = 2.0$ gives most satisfactory fuzzy classification output in many cases, the value m was depending on number of classes. It is, however, noted that the correlation coefficients were decreased when increased the fuzzy component with respect to the $m=2$. Experiments were done using the results of Blue band.

Here number of classes was changed until buildings are isolated from other features. So, one of another important problems in image classification is to guess the number of classes of an image.

FCM stops when the maximum number of iterations reached, unless objective function is optimized or not. Also, it is noticed number of iterations depended size of the data set. For effective result maximum number of iteration should be very high in numbers and it takes more time to process.

In order to compare the building detection by hard and soft classification techniques and analysis the performance of morphological operation, traditional classification techniques were applied on the same study area. This comparison was analyzed by using regression analysis on the morphological operated results independently. The testing procedures are based on the blue band results of Fuzzy C-mean clustering method (explanatory variable). It was found that the regression coefficients a_0 and a_1 (response variables) of $y=a_0+a_1x$ linear regression equation are 0.2020 and 0.4171 against the Maximum Likelihood Classifier and 0.3133 and 0.7184 against the Support Vector machine classifier. Based on the results when applying the morphological operation to

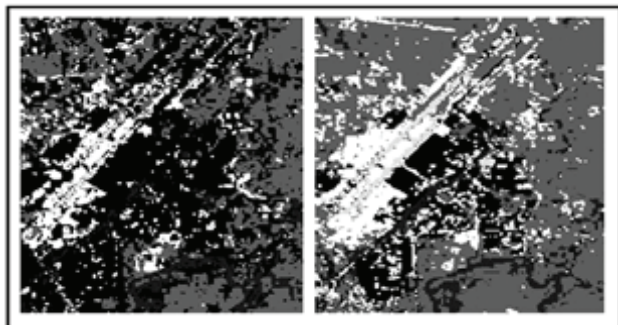


Figure 11. Morphological opening (2×2 structure element) and erode operation (1×1 structure element) for Maximum Likelihood and Support Vector Machine

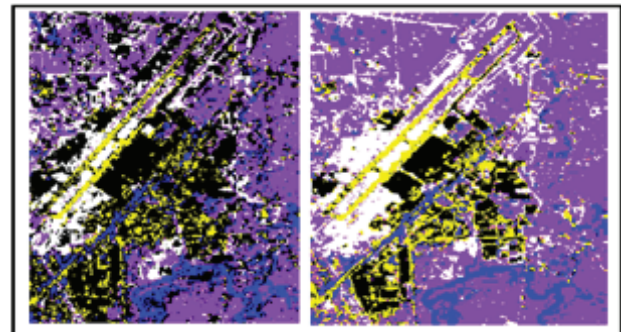


Figure 12. Maximum Likelihood and Support Vector Machine classification respectively

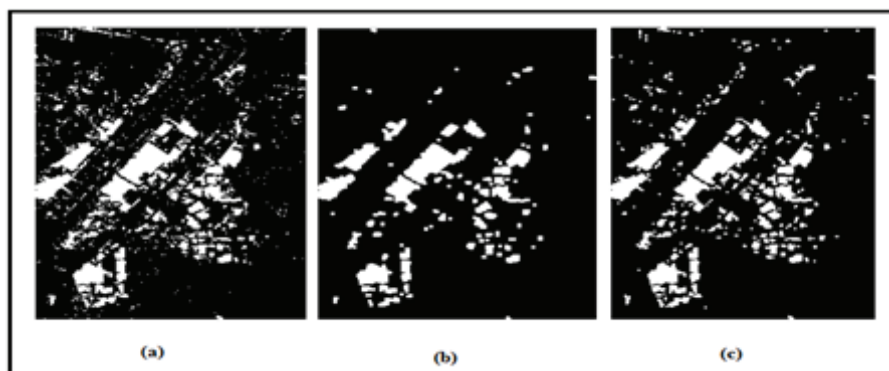


Figure 13. Fuzzy C Mean classification (b) morphological operation using 3×3 structure element (c) morphological operation using 2×2 structure element

the hard classified images, especially in coarser resolution images strong smoothing happened and buildings and most non building areas are merged together. Further in coarser resolution satellite images, single step image processing techniques are not suitable for building detection. In supervised classification, small training samples were selected carefully according to excluded the boundary pixels to overcome the short comes from mixed pixels. However, it should be mentioned, a considerable amount of pixels can be misclassified due to the assumptions that the each data point belongs to a one pure land cover class. Also when applying the regression analysis all the data points were taken in to account as explanatory variable by assuming there are no appropriate points for taking as explanatory variable.

Study area was divided into two (2) classes using Fuzzy C-mean clustering as building and non-buildings when converted from color images into grey scale image. Then the defuzzification was done using maximum membership value and result was satisfied. But after applying the morphological filtering building shape was not preserved. When changing the size of the structuring element, it is noted, according to the size and shape of the structuring element building shape has changed. So morphological image processing lies on the combination of morphological operations and structural elements. That means when a suitable operation is selected, relevant result is accessible using structural element. Yet define an effective structuring element is a difficult task.

8. Conclusion

Many researchers interest to detect buildings automatically because of their supreme role in environment. Unfortunately, it is difficult to get straightforward results with the standard image processing and classification techniques. In this study, an approach to detect buildings from low resolution satellite image using a combination of a Fuzzy C Mean clustering and mathematical morphology is proposed. The results of the corresponding techniques were presented and it evaluated there is no single method to detect building with best performance. Fuzzy clustering is a powerful unsupervised method for coarser resolution satellite images due to per pixel heterogeneity in these images. Non-building objects can be removed by means of morphological operation to some extent. After applying both techniques, it is noticed the reflectance similarity between buildings and some non-buildings are resulting in error in image classification. Beside, small gaps between the buildings may not detect correctly. Also, this method is not able to detect small buildings, even visually (especially residences). These are the major drawback in proposed method. Further, it is noticed the blue band image give a better result for building detection than red band image and also obtained result verified near infrared band is not suitable for building detection. It is obvious that the accuracy of building detection in satellite images in this study is still not high enough for a detailed investigation of the urban building development or large-scale GIS applications. Finally, we should mention that the

proposed method can be generalized to detect any kind of object in satellite images. One of the most interesting questions when considering future studies is the usefulness of high-resolution (spatial and spectral) satellite and airborne sensors for detailed research of natural and man-made features.

9. Recommendation

Still, there are open challenges to the future researches to calculate the appropriate number of clusters because the optimal number of clusters may vary with every dataset. In addition, that either objective function become minimum or not iterative procedure was stopped when the maximum amount of iteration reached. In order to overcome this short comes, integrate the fully fuzzy classification concept to improve the classification result. Experiments can be carried out on different datasets, especially for less color variation datasets. Further, directly modifying the objective function to overcome the noise sensitiveness of conventional Fuzzy C Mean clustering algorithm.

Acknowledgement

I would like to acknowledge every person who kept my confidence and spirit high during the research work.

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