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Novel Segmentation Method for Fractal Geometry Based Satellite Images Classification

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Abstract

The use of efficient image classification methods gains most interest due to its close relation with the improvements happen in the fields of compression and communications. Fractal geometry is receiving increased attention as a quantitative and qualitative model for natural phenomena description, which can establish an active classification technique when applied on satellite image. In this paper, the used satellite image is taken by Landsat for Al-Kut city in Iraq. Different parts of this image that contains different visible classes are chosen manually to be a training area. The training areas are passing two stages: segmentation and classification. To credit effective segmentation, the training areas are segmented by a hybrid technique consists of two sequenced methods: Diagonal (*Dg*) method that operated inside the quadtree (*Q*) method. The hybrid method segments each squared image block into either four quadrants or two triangular blocks according to uniformity criterion. Then, unsupervised classification is applied depending on the fractal feature. The fractional Brownian motion (*FBM*) is the fractal feature that employed for classification. The classification is implemented for each image segment; squared or triangular. The results of *FBM* are grouped into five deferent clusters; each represents distinct class of image. The center of each group and its dispersion distance are stored in a database table to be used in the classification of whole image. The classification results gave 95% classification score, which ensures the ability of *FBM* to recognize different satellite image regions when used as fractal feature.

Keywords: Box Counting; Classification; Fractal Features; Satellite Image.

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1. Introduction

Remote sensing is the use of satellite imagery to collect a specific data from the Earth about object or phenomenon without physical contact [1]. Aerial sensor technologies are used to detect and classify objects on the Earth by propagated signals (i.e. electromagnetic radiation). Remotely sensed data are contributed with information from ecosystem models to offer opportunity for predicting and understanding the behavior of the Earth's ecosystem. High spatio-temporal resolutions of sensors make the observation of precise spatial and temporal structures more accessible in dynamic scenes. Spectral and spatial dimensions combined with temporal components give a valuable information source. Such information helps to detect complex and important patterns by means applications deal with environmental monitoring and analysis of land-cover dynamics. Satellite imagery is sometimes supplemented with aerial photography for achieving an integral form about the target area. Aerial photography has higher resolution, it used for specific applications since it is more expensive than satellite imagery. Satellite imagery is sometimes contributed with vector or raster data in GIS (Geographic Information System) when the imagery needs to be spatially rectified [2]. Many applications based on using satellite imagery in a quantitative fashion require classification of image regions into a number of relevant categories or distinguishable classes. Satellite image classification is a clustering method based on image features, the classification results are represented by visualization techniques [3]. Fractal geometry provides a suitable textural image classification framework by studying the nature irregularity shapes in the image, since it allows to easily describing such fractal images. The fractal geometry can recognize small image segment that characterized by its spectral uniformity, this necessitate first to segment the image before the classification. The main characteristics of fractal images are that they are continuous but not differentiable that allows showing the fine details at any arbitrarily small scale [4].

2. Problem Statement

Fractal models have been used in a variety of image processing and pattern recognition applications. There are a great deal of focus was granted to satellite image classification based fractal geometry. The use of fractal geometry for image processing requires first segmenting the image into uniform image parts, the most dominant methods of image partitioning are the quadtree and horizontal-vertical. Both are gives square or rectangular image part, the methods of fractal feature extraction are suitable for such uniform parts of image, but they cannot able to compute fractal features for other shapes of image parts, such as circle, triangle, or non-uniform shapes. Such that, there are some uncertainty occur in the classification score due to an oblique edges that separated between different image regions.

3. Related Work and Contribution

There are many papers devoted to image segmentation and classification. They differ in many aspects such as; material images, used approach, or even the application limitations. The feasibility of using fractal geometry for image classification is investigated in the following literatures:

3.1 Related Work

Numerous approaches were developed in order to achieve the more efficient technique to serve the wide applications of field of interest; Al Ani in 2007 introduced a supervised classification for TM-multi-spectral satellite images. The traditional quadtree segmentation method was applied, then for each segmented block; the fractal features are computed and then used as maximum likelihood classifiers. The used fractal features are fractal dimension and lacunarity. The result showed that the fractal dimension do not have the ability to classify the image blocks whereas the lacunarity showed good classification results. It was found that the fractal geometry can assign efficient parameters for describing images [5], but Sun and his colleagues in 2009 presented an efficient box counting based method for improving fractal dimension estimation. Novel model is proposed for assigning less number of boxes that cover image surface at different scales, which leads to more precision of measurements. The practices of synthesized fractional Brownian motion are applied on real texture images and remote sensing images. The results showed such method can outperform the well-known differential box counting (DBC) method [6], whereas Liaw and his colleagues in 2011 used the Fractional Brownian Motion (FBM) to model the texture of the fiber surface. Fourier-domain Maximum Likelihood Estimator (FDMLE) was applied to calculate the fractal parameter of FBM. The texture of the surface of individual fiber is an important characteristic; it was classified and recognized using the surface texture by using the fractal parameter and Hurst coefficient [7]. Florindo and his colleagues in 2013 proposed descriptors extraction technique from a texture gray scale image. The method consists in modeling the image through a complex network, based on the distribution of gray-level intensities. Therefore, they process the adjacency matrix as a geometrical object and compute its fractal dimension. Thus they apply a multiscale transform over the power law fractal curve, obtaining the descriptors of the image. The method was tested in a classification task with a comparison to other classical texture descriptors. This technique achieved the best success rate in the classification of a well-known texture data set [8].

3.2 Contribution

Previous studies point out to the ability of different algorithms to achieve a desired segmentation with acceptable precision, such that triangular segmentation method is employed to establish accurate image segmentation especially at the oblique edges that separates different image regions. The contribution is modifying the method of estimating the fractal features to be applied on triangular shaped region of image. This modification promises to achieve good classification for satellite images, which can be expanded to be applied on diversity range of conceptual images.

4. Developed Classification Method

The generic structure of the developed satellite image classification method is shown in Fig (1). It is shown that method is designed to be consisted of two phases: the training and recognition. The training is an offline phase; it is responsible on collecting sample image classes to be stored as comparable models in database. Whereas the recognition is an online phase, which is responsible on verifying the test image blocks in comparison with the trained models found in the database. Both phases are composed of three stages include: image preprocessing, image partitioning, and features extraction. Features extraction attempts to estimate the fractional Brownian motion (*FBM*) for all test image blocks. Last stage is a comparison based on fractal feature between the image blocks and training classes found in the database, the result of the comparison will determine the similarity measure between the considered image blocks and then help to make the classification decision. More details about each stage are given in the following subsections:

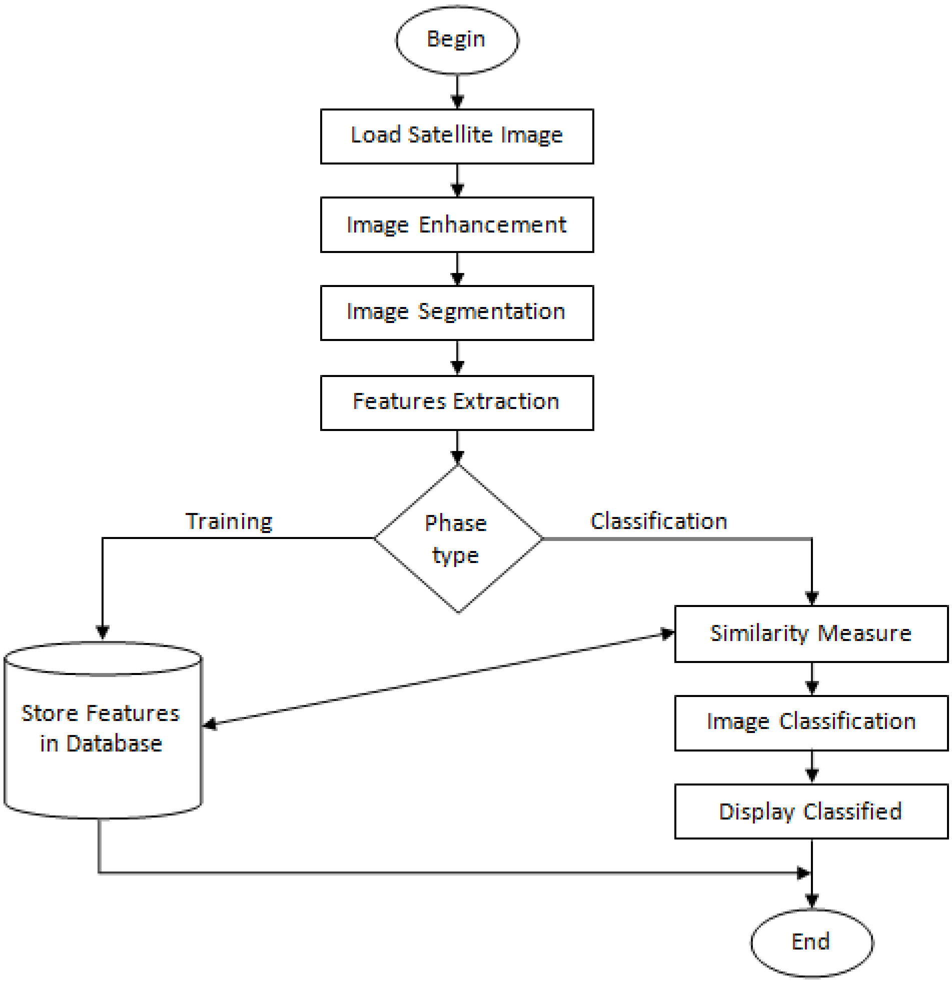


Figure 1: Block diagram of the developed satellite image classification method

4.1 Image Enhancement

Image enhancement is a preprocessing stage seeks to improve the visual appearance of the image under consideration. This stage is relied on the intensity of pixels with no effect the correlation of adjacent pixels. Such enhancement leads to improve the distinguishing between image features, which can be achieved by applying the following relation on the image:

$$I_e(x,y) = round[(\frac{I_o(x,y)-l}{h-l}) \times 255] \quad \ldots (1)$$

Where, $I_e(x,y)$ represent the new enhanced image, $I_o(x,y)$ is the original image, x, and y are indices of the pixel in the image, *l* represent the bottom 1% of all pixel values of original image, and *h* represent the top 1% of all pixel values of original image [9].

Then, the three enhanced band were concatenated together to get new gray scale enhanced image using the following relation:

$$I(x,y) = 0.2989R_e(x,y) + 0.5870G_e(x,y) + 0.1140B_e(x,y) \quad \dots (2)$$

Where, $I(x,y)$ is the grey enhanced image, $R_e(x,y)$, $G_e(x,y)$, and $B_e(x,y)$ are the pixel color components of enhanced image [10].

4.2 Image Segmentation

The novel effort in the present work is developing the diagonal (*Dg*) segmentation method inside the quadtree (*Q*) when the conditions of the *Q* are not satisfied. This novel hybrid method is called Quadtree-Diagonal (*QDg*) method. This make the image is first subdivided into squares by means quadtree, then each square either left as it or subdivided into two triangles when satisfies the conditions of the diagonal segmentation. Fig (2) shows the segmentation grid when the *QDg* method is applied on a test image.

The idea of the diagonal *Dg* segmentation is inspired from *Q* method. Therefore, same technique can be used to achieve diagonal partitioning. The diagonal partitioning method is based on computing the directional deference between the mean values of upper-lower main and semi diagonals triangles of blocks by using the following relations [11]:

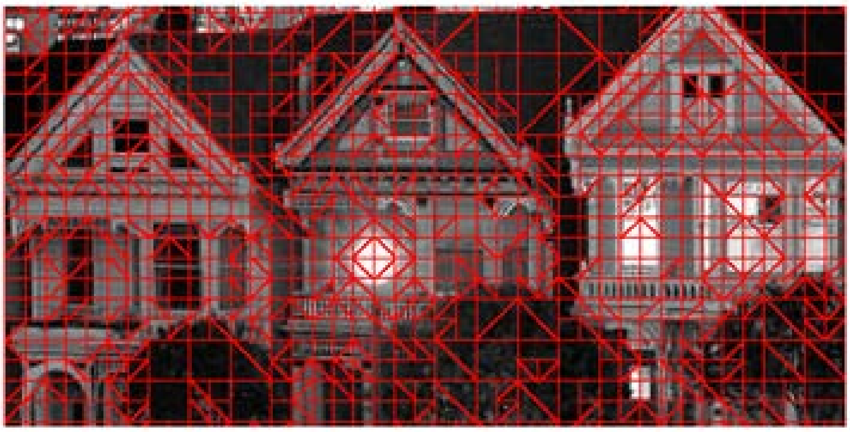
$$D_M = \left| \sum_{y=1}^{M-1} \sum_{x=y+1}^{N} I(x,y) - \sum_{y=2}^{M} \sum_{x=1}^{y-1} I(x,y) \right| \quad \dots (3)$$

$$D_S = \left| \sum_{y=1}^{M-1} \sum_{x=1}^{N-y} I(x,y) - \sum_{y=2}^{M} \sum_{x=N-y+2}^{N} I(x,y) \right| \quad \dots (4)$$

Where, D_M and D_S is the difference around main and semi diagonal axis of block respectively, *M* and *N* size of block, *x* and *y* indices of each pixel in the block and *f* the intensity of pixel. Then the large difference was checked if D_M was the largest and it was greater than a threshold value then a main diagonal partitioning decision will be taken. While, if D_S was the largest and greater than a threshold value then a semi diagonal partitioning is performed on the block. The implementation of this type of partitioning method can be demonstrated for each sub-block by checking the uniformity criterion to decide whether the sub-block will be partitioned into two halves or not, and in which direction the partitioning will be performed. The implementation of such hybrid partitioning method requires to set the following segmentation control parameters [12]:

i. Maximum block size (S_{max}).
ii. Minimum block size (S_{min}).
iii. Mean factor (β): represents the multiplication factor; when it is multiplied by the global mean (M_g) it will define the value of the extended mean (M_e).
iv. Inclusion factor (α): represents the multiple factor, when it is multiplied by the global standard deviation (σ) it will define the value of the extended standard deviation (σ_e).
v. Acceptance ratio (R): represents the ratio of the number of pixels whose values differ from the block mean by a distance more than the expected extended standard deviation.

(a) Test image



(b) Segmented image

Figure 2: Result of QDg segmentation when applied on test image

4.3 Features Extraction

The most of fractal features are related to fractal dimension, such that the computation of *FBM* requires first computing the fractal dimension.

Fractal dimension is a fraction number restricted in between the range 2-3 for two dimensional images, which may give interfered values belonging to different classes, and leads to confuse the classification results. Such that, the use of *FBM* is more suitable than the fractal dimension for describing the image regions.

The procedure of fractal dimension computation is a modified box-counting, which developed to eliminate the limitation of the traditional method. Also, the modification is adapting the boundary conditional values of the box counting method that leads to achieve distinguished values of *FBM* for each image block resulted from the segmentation stage.

4.4 Training Phase

The training phase is responsible on determining image classes and specifying the useful range of *FBM* for each concept appear in the used image. Therefore, a specific range [Min(*FBM*)-Max(*FBM*)] of *FBM* for each class should be determined and stored in database to be used in the classification of other image segments.

4.5 Classification Phase

The *FBM* is a single numerical feature that can provide a quantitative assessment for each image segment to the closest class numerically. The similarity measure (S_i) is the maximum percent value related to the normalized difference between the *FBM* that belong to ith segment (FBM_i) and the jth (FBM_j) of database, as given in the following relationship:

$$S_i = max\left[1 - \frac{|FBM_i - FBM_j|}{\sum_{j=1}^{N_c} |FBM_i - FBM_j|}\right] \quad \dots (5)$$

where, N_c is the number of classes in the database, *i* is pointer refer to the ith image segment, *j* is pointer refers to the image class in the database. The similarity measure is determined for each image segment to be assigned to the class that gives maximum similarity measure. Then, a specific color is now used for coloring each segment according to its ownership to any class. Also, there is a color legend should be fixed to explain the meaning of colors appear in the classification results.

5. Material Image and Results

The used material image want to be classified was captured by Landsat satellite. This image covered an area at the east of Al-Kut city in Iraq. Fig (2) shows the considered image, whereas the characteristics of this image are listed in Table (1). One of the most important reasons of using this image is the different geographical landmarks appears in the image, which leads to different classes found in the image.

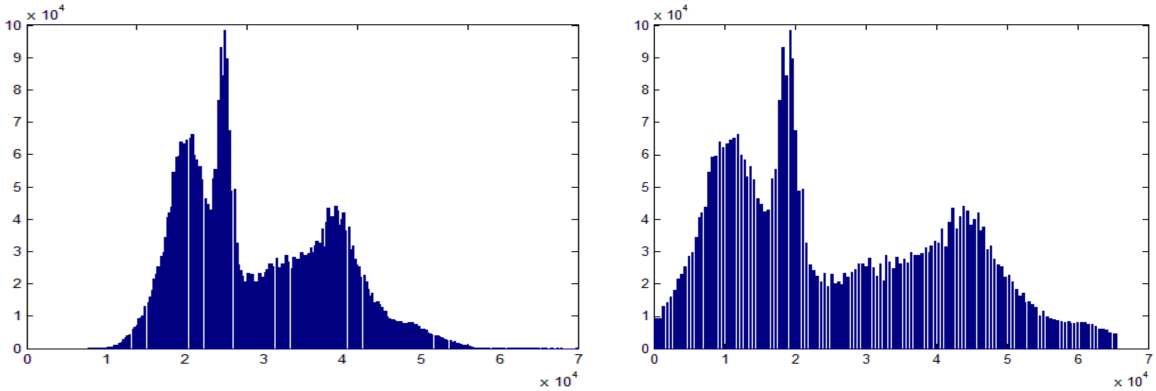
This image covered a land area of about 1.024×1.024*km*, and contained a variety image features. Actually, the geographical region demonstrated in the image was visited to detect the types of the landcover found in the study area. It was found that there are five distinct classes: water, bare land, farm land, perpetual plants and paved area. Also, the field visit enables to determine the type and sites of the training areas. True training areas lead to correct classification results.

Table 1: Characteristics of used satellite image.

Date of Capture	2010
No. of Bands	3 (RGB)
Spatial Resolution	0.5m
Radiometric Resolution	16 bit
Projection System	WGS_1984_UTM_Zone_38N
covered area	1.024×1.024km
Columns × Rows	2048 × 2048pixels
Rectangular Coordinates	Top= 3602650.040m Bottom= 3601625.858m Left= 584663.581m Right= 585688.263m
Geographical Coordinates	North= 32° 33' 28.9" South= 32° 32' 55.36" East= 45° 54' 45.85" West= 45° 54' 6.23"

Figure 3: The considered material image.

The application of enhancement stage on the considered image leads to best distribution for image color, Fig (3) shows the histogram of the image before and after enhancing the color. Also, Fig (4) shows the color image resulted from applying equation (1) on each color band of the considered image, while Fig (5) shows the enhanced image resulted from applying equation (2), which is directly forwarded to the segmentation stage. Fig (6) shows the selected training areas enclosed by a squared frame. It is shown that the selected training areas are belonging into different contents region of image, each of them gives distinguished image class when determining the classification feature (i.e. *FBM*). Table (2) list the minimum and maximum values of the fractal feature *FBM* that used to determine the extended range of the *FBM* for each class in the database store. Furthermore, Fig (7) shows the results of *QDg* segmentation method applied on the considered image, whereas Fig (8) shows the results of the proposed classification method.



A. Before Quantization **B.** After Quantization

Figure 4: Histogram of enhanced Image

Figure 5: Colored enhanced image.

Figure 6: Gray enhanced image

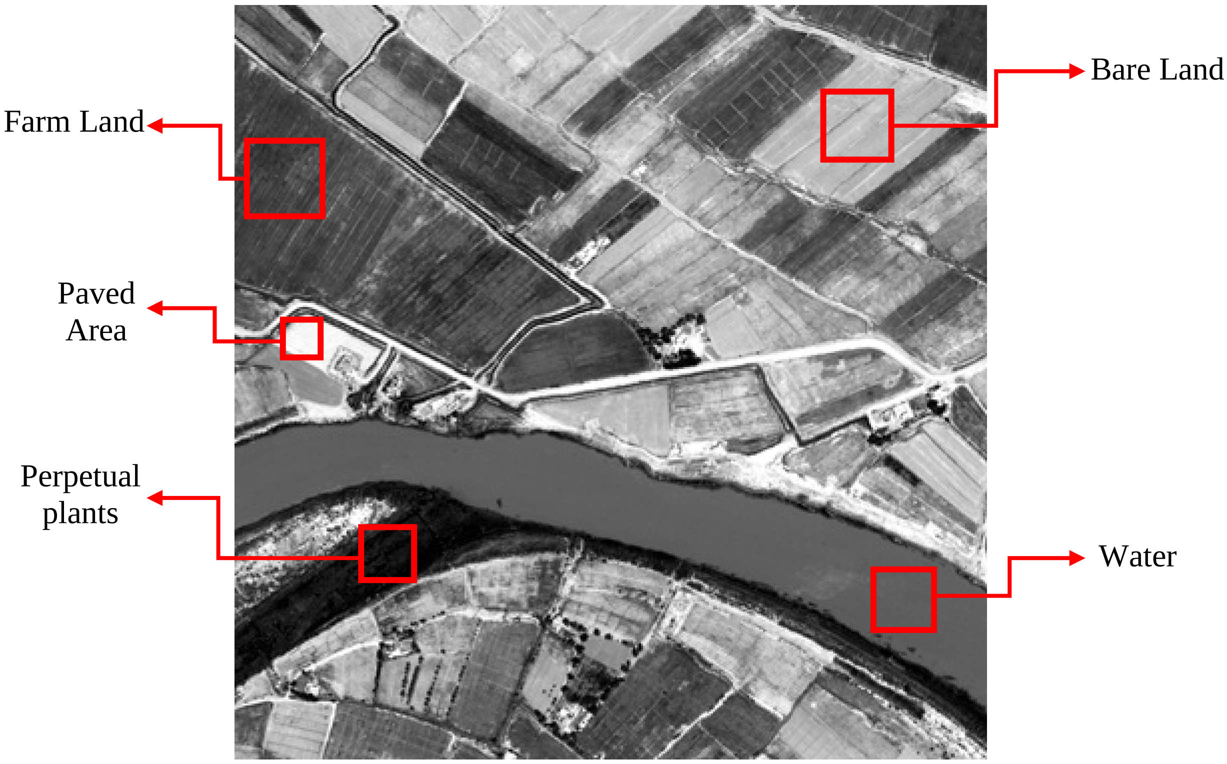


Figure 7: Training areas of the considered image.

Table 2: Extended ranges of *FBM* values for each image class.

Classes	FBM_{Min}	FBM_{Max}
Water	0	0.152738
Bare land	0.152738	0.317352
Farm land	0.317352	0.582846
Perpetual plants	0.582846	0.825389
Paved area	0.825389	1

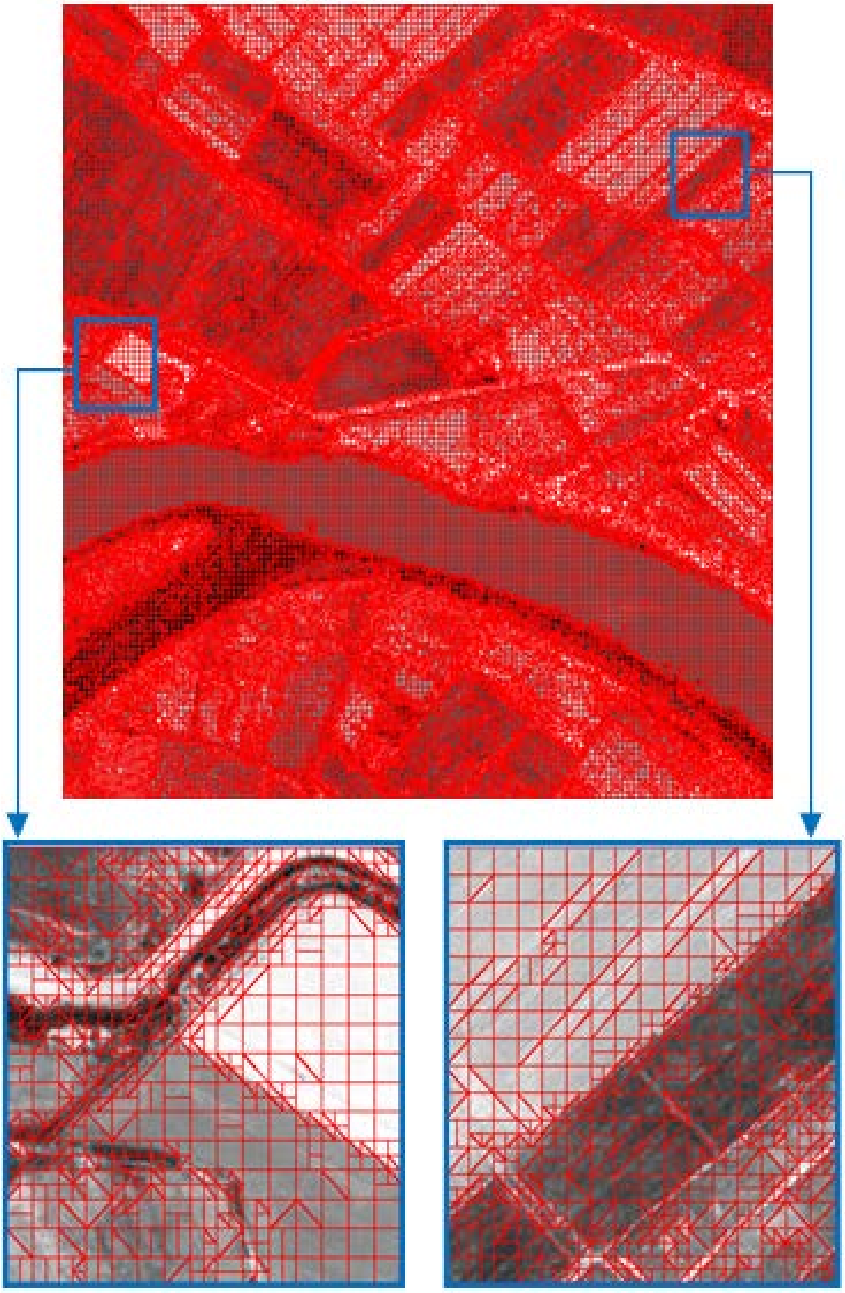


Figure 8: result of QDg segmentation method applied on the considered image.

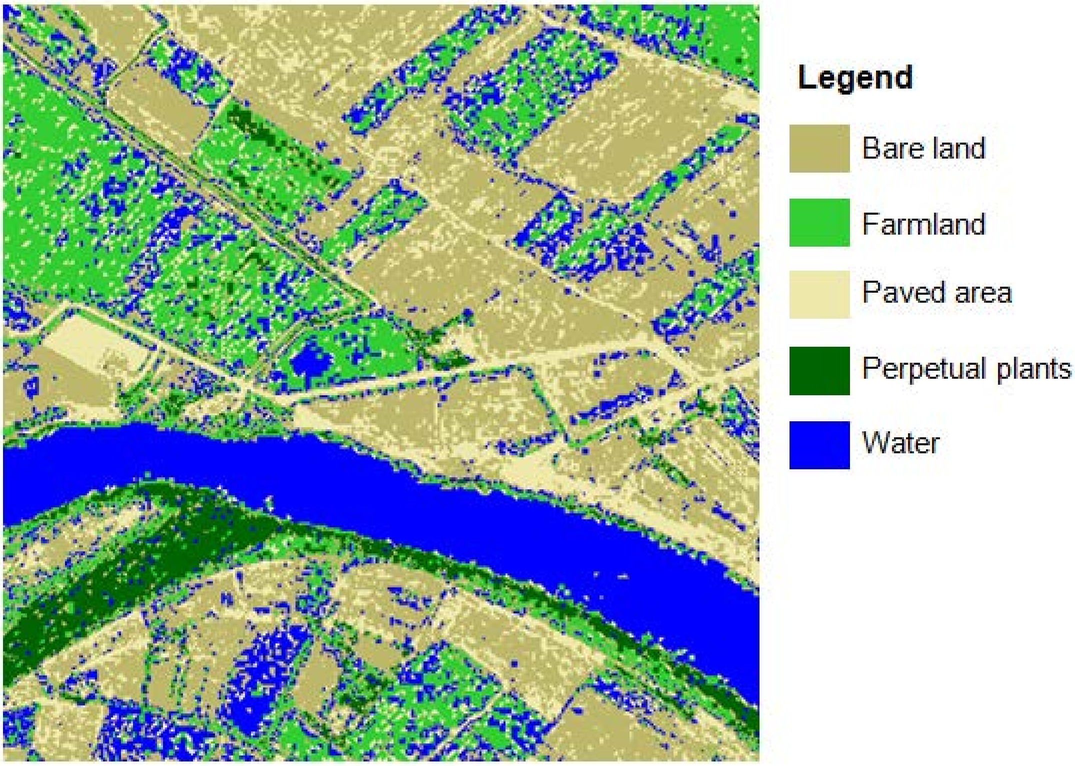


Figure 9: Classification Result of the considered Image

6. Results Analysis

The field visit and stand on the ground of study area make sure by reliance other information about covered area, such as, recently aerial images and thematic maps, reconnoitering zone or any earlier information related to the study area. This was useful when evaluating the classification process by comparing the classification results with the actual information achieved throughout the field view.

Results observation shows that the image regions of fine details were segmented into squares by quadtree, while the regions that contain oblique edges were segmented into triangles by the Dg method. The size of each segment was automatically determined according to the spectral details variety. Almost, image segments take a small size at the region of more details, whereas it is became relatively larger at few detailed region. The true segmentation makes the application of fractal based classification to be more confident. Indeed, the chromaticity do not greatly serves the classification of satellite images, so the classification found occurred just depending on the spectral variety. It was seen that the gray images are classified according to the spectral variation appeared in the image. Since the image contained extended regions of different concepts, each class was fitted to include a specific region. Such that, the FBM was found classify the image segment in terms of the dominant concept of it. This ensures the ability of the image segmentation based on *QDg* to make accurate classification since it is related to the image segmentation into squares or triangles in terms of spectral details and intensity distribution. The fractal feature *FBM* gave encouraging classification results, where each class of image has a relatively different range of *FBM*. Such that, fractal technique appear well suited to the analysis of textural features in remotely sensed images, as the environmental features captured in the image are often complex and fragmented. In general, the FBM method for classification purposes was successfully indicating actual results to classify satellite images, which ensure the efficiency of the employed method and the good performance of the classification.

7. Conclusions

Throughout the implementation of the present work, a number of conclusions have been achieved based on the practical results. The following statements summarize the most important ones:

1. The high classification results prove that the fractal geometry exhibit the description of satellite images.
2. Higher accuracy of fractal dimension estimation is achieved by allowing the height of the box at the top of each grid block to be adaptable to the maximum gray-scale of that block and the method is applicable to blocks with arbitrary sizes and shapes.
3. The uniformity of blocks' characteristics which produced by the suggested segmentation method leads to get independent range of D_F for each class. This has increased the accuracy of the classification.
4. The convergence in D_F for different phenomena and the smallness of the range of it caused to decrease the efficiency of classification.

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