

Genetic Algorithm Based Image Integration for Multiband Satellite Image Classification

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Abstract— The motivation of this paper is to establish an accurate method for multiband satellite image classification. Different imagery bands with predefined training areas are considered to test the proposed classification method. The genetic algorithm (GA) is first employed to evolve newly integrated image with more information and best contrast. The information of the used image bands are transferred across generations to be concentrated in one integral image. Then, the integrated image is segmented into variable blocks size using hybrid segmentation (HS) method to make spectrally homogenous image blocks. The fractal features are estimated for each block to determine the image classes that stored as comparable models in dataset dictionary. Then, the integral image is classified pixel by pixel in comparison to the information given in the dataset. The classification results are found identifying the actual training data, which ensure the success of the proposed method and the effective performance of the classification.

Keywords — genetic algorithm, Image integration, Satellite image classification, pixel based classification, Image segmentation.

1. INTRODUCTION

Satellite Image classification is an interesting problem in image analysis field; it plays a significant role in image processing due to its difficult dealing, which come from visual diversity that leads to computation complexity. The main goal of image classification is to divide the image into homogeneous regions delimited by boundaries in order to separate the different visible entities in the image. The classification aims to label the various visible components in an image. Many classification methods had been proposed in the last three decades, the problem remains related to benchmark of these methods and estimate their robustness in terms of a given real life application [1].

Newly, metaheuristic algorithms are employed by many researchers to solve many problems related to image processing. Metaheuristic algorithms are set of algorithmic concepts that modified to define heuristic method and make it useful in the fields of application. Such that, a metaheuristic is described as a general purpose heuristic method is established to guide an interesting problem toward promising regions in the search space with high quality solutions. Therefore, a metaheuristic is a general framework of algorithms that can be applied for optimizing different problems with relatively few modifications to fit the specific task [2]. Metaheuristics gains significant attention due to its ability of finding high quality solutions, and practically relevant combinatorial optimization problems in a reasonable time. This is particularly true for large and poorly understood problems. There are many metaheuristic algorithms such as Genetic Algorithms (GA) [3], Tabu Search and Simulated Annealing [4], have been employed to deal with the

computationally intractable problems. Genetic algorithm (GA) is a valuable metaheuristic developed for composing approximate solutions [5], it was receiving extensive attention due to its successful applications to many combinatorial optimization problems [6]. GA like simulated annealing, it fosters its solution strategy through the use of nature metaphors. The GA is based upon the behaviors of generation that exhibit when looking for a path to the advantage of their improvement. Also, GA is like simulated annealing or Tabu search, in which a multi agent are deployed for each generation, each agent has its individual decision made based upon collective memory or knowledge. Recently, the GA metaheuristic has been candidate to provide a unifying framework for most applications of heuristic algorithms to combinatorial optimization problems. Algorithms that actually are instantiations of the GA metaheuristic will be called GA algorithms. This paper aims to investigate the ability of the genetic optimization for solving the problem of satellite image integration in order to classify varsity areas in such images [7].

2. PROBLEM STATEMENT

The general behavior of most satellite image classification methods is not look at the fine details or boundaries of different spectral regions; they observe the main cues those dominant fine details. Almost, these methods are implemented according to some considered restrictions that help to achieve acceptable results. The motivation we address in this paper is to overcome the problem of passing the fine details; this is carried out by using the genetic algorithm for satellite image integration. Image

integration makes the fine details to be shown clearly, such that good classification can be achieved. Moreover, to credit efficient classification, a hybrid partitioning method is employed in the training phase. Hybrid method uses triangle partitioning method inside the quadtree method to credit best partitioning that showing more spectrally homogenous parts. The use of triangle method credits partition image parts that include inclined boundaries within. As a result, good partitioning of optimized integral image promise to makes well classification.

3. RELATED WORK AND CONTRIBUTION

The problem of satellite image classification has attracted a lot of research. The applications field was still searching about an accurate method that can be used to improve the classification results. The most interested researches besides our contribution are briefly explained in the following subsections:

3.1 Related Work

There are many papers were devoted to image classification. They are different in many aspects such as; used images, adopted approach, or even the limitations of application. In the following, we focus on some researches that dealing with the considered problem of enhancing image details for purpose of classification in different application field:

The feasibility of using genetic algorithm for segmenting satellite images was investigated in [8], a lot discussion for issues involved in designing such algorithms are presented. This leads to find a genetic supervised classification technique to establish automatic feature extraction algorithms that proposed in [9] using multibands imagery technique, which records acceptable results were achieved by ant colony optimization (ACO) method. Also, an automatic construction of image classification based on genetic image neural network for image classification (GIN-IC) was proposed in [10]. This technique transformed multibands image to easier-to-classify image using nodes transformation, and selects adequate image features using feature extraction nodes. It showed the use of image transformation nodes is effective for the problem of multibands image classification. Recently, an evolutionary computing based on fractal image compression was introduces in [11]. The use of evolutionary computing was employed to achieve good partitioning, which showed the best rate in the distortion curve was obtained in comparison to traditional quadtree partitioning.

The researches based on evolutionary algorithms include satellite and landcover imaging, the literature in [12] proposed suitable design of image processing procedure is preparing for successful classification of remotely sensed data into a thematic map. The improvement of classification accuracy depends on the essential use of multiple features of remotely sensed data and the selection of suitable classification method. The probability densities associated to image pixel intensities within each image region are considered in [13] to be completely unknown priorities.

The problem of information optimization was solved by deriving the associated gradient flows and applying curve evolution techniques, which showed the acceptable experimental results based on both synthetic and real images are lead to prove that the proposed technique can solve a variety of challenging image classification problems.

Many studies based on evolutionary algorithms were found in the field of object recognition and segmentation. New segmentation method was proposed in [14] using a pixel clustering subsystem as a part of segmentation. This provided contextual information related to the objects that want to be segmented. The motivation was to segment and classify follows the wrapper methods of feature selection. It showed the efficiency of wrapper-based segmentation on real-world and complex images of automotive vehicle occupants. Moreover, the experiment mentioned in [15] proved the particle swarm optimization (PSO) is suitable for extracting individual features, which leads to prove that the evolution of associated weak classifiers is more effective than for selecting features.

In addition, the evolutionary methods employed in the field of computer aided diagnosis; some achievements were obtained depending on some tests that ensure the ability of the evolutionary algorithms to give high efficient classification. An intelligence algorithm based on swarming-agent was proposed in [16] using a hybrid ACO and PSO algorithms to identify the diagnostic proteomic patterns of biomarkers for early detection of ovarian cancer. The proposed system was also gives another opinion for the pathologist related to the condition of the ovary. The robustness of this method comes from the less field of view of the imagery system. Also, the automated diagnosis research was handled in [17] by establishing software system of expert breast cancer diagnosis. This system consists of three steps of cytological image analysis. First step is segmenting cell tracking using an active contour, and then isolate the nucleus the cell. The textural features of this nucleus are extracted using the wavelet transforms. Such that, malign texture are distinguished from benign depending on the assumption that tumoral texture is different from that of other kinds of tissues. The textural features are formed as input vector of Multi Layer Perceptron (MLP) for classifying the image into malign and benign. Then, Kohonen self-organizing map of neural network is used to achieve unsupervised image classification. In [18], two dimensional discrete wavelet transforms applied on selected regions of magnetic resonance images (MRI) for denoising approximation purpose. The neural network is first trained with test images, and then used to classify pixels of original image. This technique showed promising performance for the problem of MRI image classification.

3.2 Our Contribution

Previous studies referred to the robustness of evolutionary algorithms to obtain desired solutions with high precision, therefore genetic algorithm (GA) is handled to establish an

accurate satellite image classification. The contribution in this work is the employment of genetic algorithm to integrate the image cues before the image partitioning. The integrated image pass through hybrid segmentation (HS) method, which is inspired from the quadtree segmentation (QS) method, the adaptation of HS summarized by including the triangle segmentation (TS) method inside the well-known QS method. HS method goes to partition the target image into variable size parts of regular or oblique boundaries. Such method possesses some benefits over the quadtree, which is the high accuracy of partitioning in regions that contains inclined edges belong to different classes; this guarantees the acceptable homogenous part of image. Such partitioning paved the way for the fractal classifier to determine best dataset that leads to proper image classification.

4. FRACTAL GEOMETRY

Fractal geometry provides a suitable satellite image classification framework by studying the nature irregularity shapes since it allows to easily describing such fractal images. The fractal geometry can recognize small segment of image that characterized by its spectral uniformity, this necessitate first to segment the image before the classification [19]. The main characteristics of fractal images are that they are continuous but not differentiable and that they show a fine detailed at any arbitrarily small scale. A fundamental concept of fractal geometry is the fractal dimension, at any fractal application, one can use the fractal dimension as a recognizable fractal feature because it is a measure of complexity in fractal patterns, the higher fractal dimension the more complex the fractal pattern [6]. Because the fractal dimension F takes non-integer (i.e., $2 < F < 3$) number it is difficult to recognize plenty of classes well. Mandelbrot suggest another fractal measure call it lacunarity to handle the case of sharing two different classes with same fractal dimension. Later, lacunarity is used as a similarity measure to distinguish two fractal sub-images. Lacunarity is a set of points (curve) computed by the box counting method, which is the same method of computing the fractal dimension. Box counting method is a common and accurate one for computing the fractal dimension and the lacunarity, but it has some of complexity. The fractal dimension F of a set S contained in R_n is estimated for B^2 sub image (leaf) $B > 0$, by assuming $N_B(S)$ is the minimum number of η -dimensional cubes of side B needed to cover S . if there is a number F so that [20]:

$$N_B(S) \approx \frac{1}{B^F}, \text{ as } B \rightarrow 0 \quad \dots (1)$$

Note that the fractal dimension is F if there is some positive constant C [8].

$$\lim_{S \rightarrow 0} \frac{N_B(S)}{1/S^F} = C \quad \dots (2)$$

Since both sides of above equation are positive, it will still hold if one takes the logarithm of both sides to obtain [8]:

$$\lim_{S \rightarrow 0} \left(\ln(N_B(S) + F \times \ln(S)) \right) = \ln(C) \quad \dots (3)$$

Solving for F gives:

$$F = \lim_{S \rightarrow 0} \frac{\ln(C) - \ln(N_B(S))}{\ln(B)} \quad \dots (4)$$

$$F = -\lim_{S \rightarrow 0} \frac{\ln(N_B(S))}{\ln(B)} \quad \dots (5)$$

Note that $\ln(C)$ drops out, because it is constant while the denominator becomes infinite as $B \rightarrow 0$. Also, since $0 < B < 1$, $\ln(B)$ is negative, so F is positive as one would expect. The lacunarity is now given as [8]:

$$L = E \left[\left(\frac{M}{E(M)} - 1 \right)^2 \right] \quad \dots (6)$$

Where, L is the lacunarity, $E(M)$ is the expectation value, and M is the mass of the intersection of the considered set with a box of size B . This definition measures the discrepancy between the actual mass and the expected mass. Besides, since M depends on B we have that lacunarity depends on B , too [20,21]. For each segmented block, the lacunarity is assumed to be a classifier parameter. So, it is expected the different neighbor blocks lead to make their extracted features have recognizability among other blocks.

5. GENETIC ALGORITHM

Genetic algorithm is an efficient search algorithm that simulates the adaptive evaluation process of natural system. It has been successfully applied to many complex problems such as time scheduling optimization and traveling salesman problems [22]. Each individual in the GA population represents a possible solution to the problem. Finding individuals, which are the best suggestions to any problem and combining these individuals into new individuals, is an important stage of the evolutionary process. Using this method repeatedly, the population hopefully evolves good solutions. Specifically, the elements of GA are: selection (according to some measures of fitness), crossover (a method of reproduction, "mating", the individuals in the current generation into new individuals in the next generation), and mutation (changing a random selected genes). The following algorithm shows the basic steps of the GA [10].

- Initialization:** Input population of N chromosomes
- Do While** the stop condition is not satisfied
- Evaluate:** the fitness $g(x)$ for each chromosome x in the population
- Do While** the new population not completed
- Selection:** Select two parent chromosomes from a population according to their fitness
- Crossover:** with a crossover probability, crossover the two parents to form a new offspring (children)
- Mutation:** with a mutation probability, mutate new offspring
- Accepting:** place new offspring in new population
- End while**
- Replace:** Use new generated population for father runs
- End while**
- End.**

6. PROPOSED CLASSIFICATION METHOD

The generic structure of the proposed method for satellite image classification using genetic algorithm based image integration is shown in Figure (1). It is shown that the proposed method is designed to be consisted of two phases: enrollment and

classification. Both phases are passing through one preprocessing stage, it is image enhancement. The enrollment phase concerned with collect the dataset samples of image classes to be stored in dataset array (referred as A) to be used as a comparable models in the classification phase. There are multi stage found in the enrollment phase, they are: image partitioning, image integration, image segmentation, fractal features extraction, then features clustering and dataset formatting and storing. Whereas the classification phase is responsible on verifying the contents of the test image in comparison with the dataset models, this is carried out by classifying the considered image pixel by pixel depending on the comparison of each pixel with the dataset models of the dataset. More details are explained in the following subsections.

$$F_e = aF_p + b \quad \dots (7)$$

Where, a and b are the linear fitting coefficients given in the following equations, in which Min_1 and Max_1 are the minimum and maximum values of pixels found in transformed image, whereas Min_2 and Max_2 are the intended values of the minimum and maximum of output image pixels.

$$a = \frac{Max_2 - Min_2}{Max_1 - Min_1} \quad \dots (8)$$

$$b = \frac{Max_2 \times Min_1 - Max_1 \times Min_2}{Max_1 - Min_1} \quad \dots (9)$$

6.2 Enrollment Phase

The enrollment of dataset is an important step for image classification. It is used for determining the image classes depending on sequenced stages. It is intended to uniformly partition the enhanced image (F_e) into equal blocks of size (B_s). The genetic algorithm is applied on the partitioned image to produce an integral image. The integral image is then segmented by HS method into spectrally homogenous segment. The fractal features are extracted from each segment, and then K-Means algorithm is used for grouping these features and then determining the best clusters (centroids) within the resulted features. The average of the image segment that belongs or closes to each centroid is stored in dataset array to be used in the classification phase. More details about the enrollment phase are explained in the following subsections:

A. Image Partitioning

Image partitioning is a process of dividing each image band into square blocks of uniform size (B_s). This process does not concerned with the spectral distribution of the image, it is just geometrical partition. In this stage, the size of block depends on the amount of spatial resolution of the image. It taken in account that low resolution image is divided into a number of blocks is less than that of higher resolution image, this is for credit enough information are containing in each block. Figure (2) shows the uniform partitioning of a satellite image.

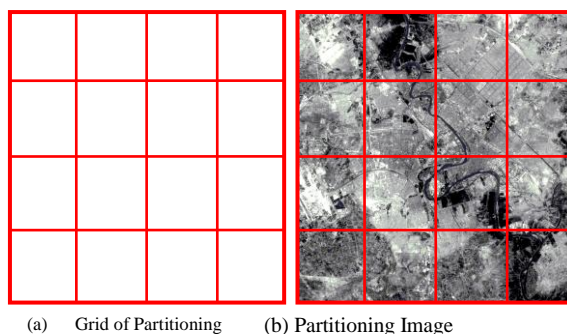


Figure (2) Uniform image partitioning.

B. Image Integration

The use of different imagery bands lead to get different details about landcover that pictured by the image. This enable to collect greater details to be represented in one image using GA.

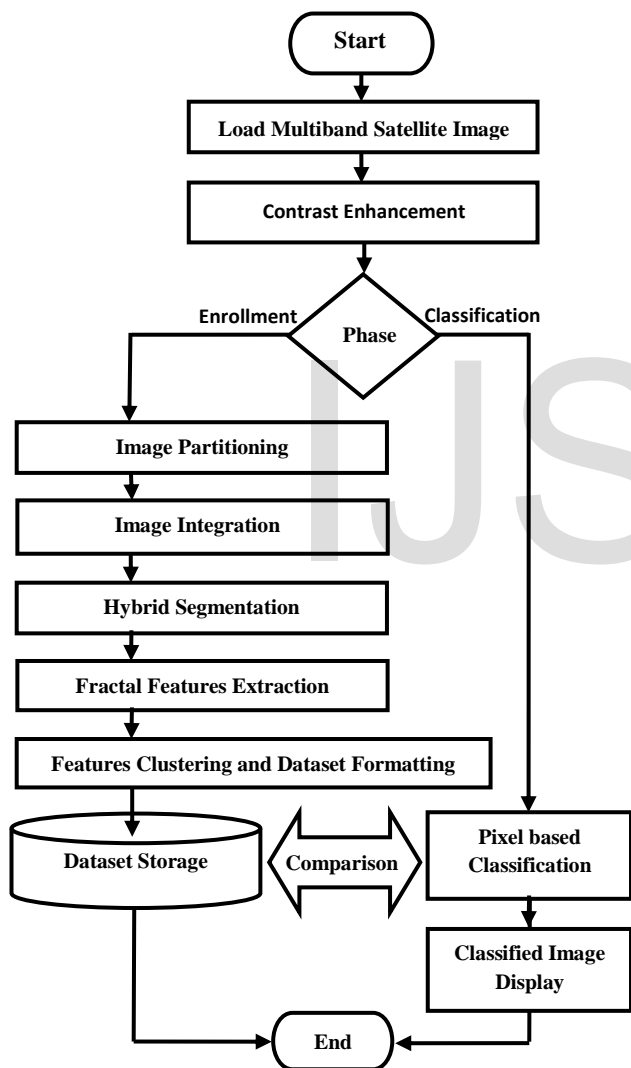


Figure (1) Block diagram of proposed classification method.

6.1 Contrast Enhancement

This stage is adopted to increase the contrast of the given prepared image. Contrast stretching is used to enhance the appearance of image details, which can be achieved by adopting the linear fitting applied on the input image F_T for achieving the output image F_p as given in the following equation:

In this stage, the considered population is the partitioned image bands; each individual band represents one chromosome in the population. GA is applied on assumed population to create best new generation that containing at least one more informatic image band. In which, the dispersion coefficient (D_c) of each image part belongs to a specific chromosome is the gene (feature) that adopted in the crossover step of GA. The D_c of image part (f_{ij}) is computed according to equation (22), which indicates the amount of the information found in each image part.

$$D_c^k = \frac{\sigma^2}{\mu} \quad \dots (10)$$

Where, μ and σ^2 are the mean and variance of k^{th} image part of size B_s , as given in the following equations.

$$\mu = \frac{1}{B_s^2} \sum_{i=0}^{B_s-1} \sum_{j=0}^{B_s-1} f_{ij} \quad \dots (11)$$

$$\sigma^2 = \frac{1}{B_s^2} \sum_{i=0}^{B_s-1} \sum_{j=0}^{B_s-1} (f_{ij} - \mu)^2 \quad \dots (12)$$

The first generation possess two dimensional array of genes for each chromosome, the size of this array is equal to the resolution $W*H$ of the image band divided by B_s . In the crossover step, the choice of any two chromosomes is randomly carried out, while the fitness function is applied on the two genes of the two crossover chromosomes. The fitness function candidates the greatest D_c as a better gene to be crossover between two chromosomes in current generation. The crossover of gene implies crossover the image part between the used parent bands. Next generation will contain better genes with same number of populations; the chromosomes will be enhanced with progressing generations. When the continuing condition is terminated, a number of generations are found in which the last generation containing the best chromosomes. Also, the greatest dispersion coefficient (D_c) of the chromosomes in the last generation will determine the integral image. In such case, the integral image is shown more descriptive than others. It shows dense information and best contrast, and ready to apply the segmentation stage on.

C. Hybrid Segmentation

The hybrid segmentation (HS) method consists of two segmentation methods: quadtree and diagonal. The diagonal (Dg) segmentation method work inside quadtree (Q) when the conditions of the Q are not satisfied. The Dg method inspired of Q method, in which same conditions are applied after developing the direction of the partitioning. Such that, the Q method segments the parent image block into four squared quadrants, while the Dg method segments the quadrant into two triangles along the principal or secondary diagonal of the quadrant according to the segmentation conditions, as shown in Figure (3). 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 [23]:

$$D_M = \left| \sum_{y=1}^{M-1} \sum_{x=y+1}^N I(x, y) - \sum_{y=2}^M \sum_{x=1}^{y-1} I(x, y) \right| \quad \dots (13)$$

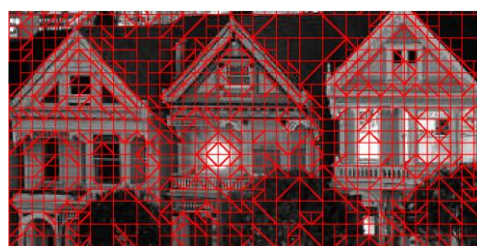
$$D_S = \left| \sum_{y=1}^{M-1} \sum_{x=1}^{N-y} I(x, y) - \sum_{y=2}^M \sum_{x=N-y+2}^N I(x, y) \right| \quad \dots (14)$$

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 [24]:

- 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 (3) Example on HS method.

D. Fractal Features Extraction

The most of fractal features are the fractal dimension (F) and lacunarity (L). Fractal dimension is a fraction number in between 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 lacunarity with it will increase the description of the image regions. The lacunarity is a set of points distributed according to the information carried by the fractal dimension. Both F and L are computed by box-counting method given in [24], the modification carried out on the box counting method to be able for computing the F and L for triangular image region is given in [25]. The modification includes adapting the boundary conditional values of the box counting method that leads to achieve distinguished values of F for each image segment. The F and L of each image segment are input to the next clustering stage.

E. Features Clustering and Dataset Formatting

In this stage, image segments are transferred from the spatial space into two dimensional parametric space (i.e., features space), in which each segment is described by the two adopted features: F and L . Then, K-Means algorithm mentioned in [17] is applied on all image segments in order to groups them according to the two descriptive features. The number N_c of groups (or clusters) indicates the number of classes found in the image. To credit understood implementation of K-means, both adopted features are normalized. The distance between current image segment and each centroid in the features space is computed as follows:

$$d_{k,j} = \sqrt{(F_n^k - F_o^j)^2 + \frac{1}{S_{max}} \sum_{n=1}^{S_{max}} (L_n^k - L_o^j)^2} \dots (15)$$

Where, $d_{k,j}$ is the distance in the feature space between the k^{th} image segment and j^{th} centroid, F_n^k is the normalized fractal dimension of the k^{th} segment, L_n^k is the normalized lacunarity of the k^{th} segment, F_o^j is the fractal dimension of the j^{th} centroid, L_o^j is the lacunarity of the j^{th} centroid, and S_{max} is the box size that determined by box counting method, which represents the number of elements in the lacunarity curve.

Dataset formatting deals with output centroid of K-Means procedure. The average of the image segment that possess features are corresponding or closest to features of j^{th} centroid is stored in one dimensional dataset array (A) in the j^{th} location as given in equation (16). In such case, each block is converted into one value stored in A . Such that, the length of A vector is equal to the number of classes (N_c).

$$A_k = \frac{1}{h \times w} \sum_{i=0}^{h-1} \sum_{j=0}^{w-1} f_k(i,j) \dots (16)$$

The average distance (d_a) between each successive two values in A is determined to be employed as a measure for detecting if the pixel within the range of a specific class or not.

6.3 Classification Phase

The classification phase can be operated after completing the enrollment phase. It can be achieved by using either results of K-means clustering or pixel comparison classification. The pixel comparison classification is a pixel-based method that depends on

the comparison of spectral value of each pixel with the established models in dataset array A , and it depends on the proximity of each pixel into the available classes in the dataset array A . The classification is carried out by computing the similarity measure (S_k) between each pixel in the integral image $F(i,j)$ and the means A_k as given in equation (26), The maximum value of S_{m_k} refers to the class that image pixel is belonging to.

$$S_{k,ij} = 1 - |A_k - F(i,j)| \dots (17)$$

7. EXPERIMENTAL RESULTS AND ANALYSIS

The multiband satellite image used in the classification was capture by Landsat satellite; it covers geographical area of Baghdad city in Iraq. Figure (4) shows the six bands of used satellite image. The resolution of these bands is 1024x1024 pixels, which carried acceptable range of informatic details about the considered image. One of the most important factors of using the Landsat Baghdad image is the different concepts of landcover appears in the image, which leads to different classes found in the image. There is a little change was found in the six bands after applying the contrast enhancement stage. Then, each image band is uniformly partitioned into squared blocks of size 4x4 pixels. This block size is suitable for such spatial resolution of image. The application of GA on the considered six bands yields the integral image shown in Figure (5). It is noticeable that the integral image has more contrast and more visual details in comparison with the six image bands.

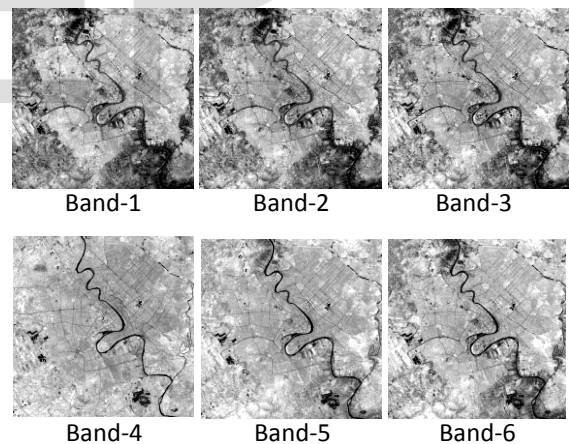


Figure (4) The used six bands of Baghdad city.

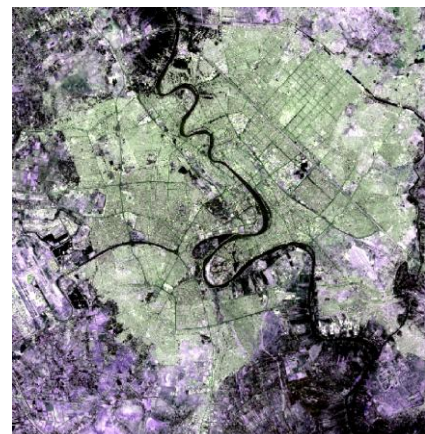


Figure (5) Integral image resulted from GA.

Figure (6) shows the results of HS segmentation method applied on the considered image, more clearly segmentation is shown in Figure (7), which is a large viewed portion of the segmented image that enclosed by square frame in Figure (6). Results observation showed 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 diagonal 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 clustering to be more confident.

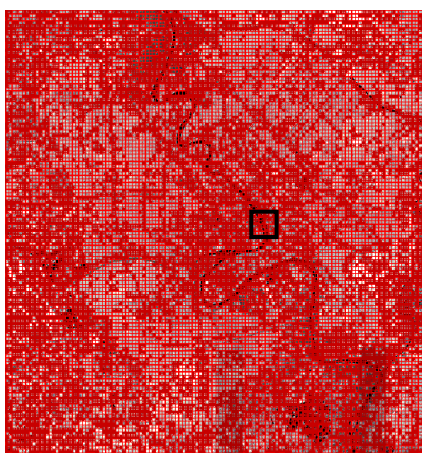


Figure (6) Results of HS segmentation applied on the integral image.

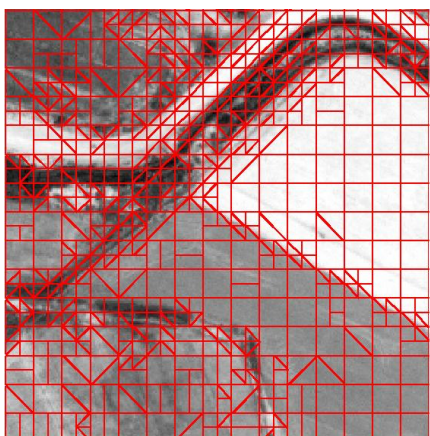


Figure (7) large viewed portion from the segmented image shown in Figure (6).

The estimated fractal dimension and lacunarity showed good discriminant behavior when applying K-means for clustering image segments depending on the fractal features. The results of the fractal dimension (F) values and lacunarity (L) curves of the five centroids are given in Table (1) and Figure (8). Table (2) presents the five values of the dataset models. It is observed that

dataset had contained different classes, which confirms the correct path of clustering, where the resulted classes were far away from each other by a distance along the grey scale depending on the details of each class. The range between the maximum and minimum values is 100, which is divided into five ($N_C=5$) of regions each of which extended by a maximum distance is equal to double d_a . Practically, it is found that the estimated value of d_a is equal to 24.4826. Thus, the distance separated between each two successive values in the dataset A is ($2 \times 24.4826 = 48.9652$).

Table (1) Resulted fractal dimension (F) of the five centroids.

Centroid	F
C1	1.8936
C2	1.7163
C3	1.6346
C4	1.5275
C5	1.4836

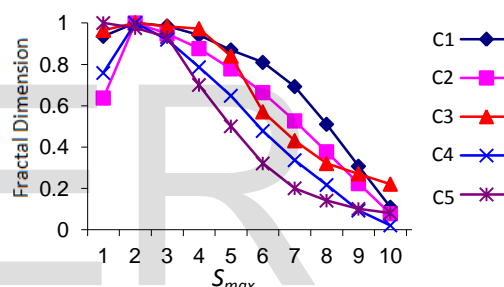


Figure (8) Resulted lacunarities of the five centroids.

Table (2) Resulted values of dataset models.

Class	A
1	47.8652
2	97.9334
3	146.8956
4	196.8608
5	244.922

The study area was visited to determine the available classes found in the considered image. It was found that there are five distinct classes; water, vegetation, Resident with vegetation, Resident without vegetation, and Open Land. Let we denote these classes as C_1 , C_2 , C_3 , C_4 , and C_5 respectively. The classification result of the integrated image using the results of K-means clustering is shown in Figure (9), in which each image block is classified in terms of its belonging to any centroid (i.e. class), such classification is block based method. Whereas the results of the comparison of each image pixel with the dataset is shown in Figure (10), which is a pixel based classification.

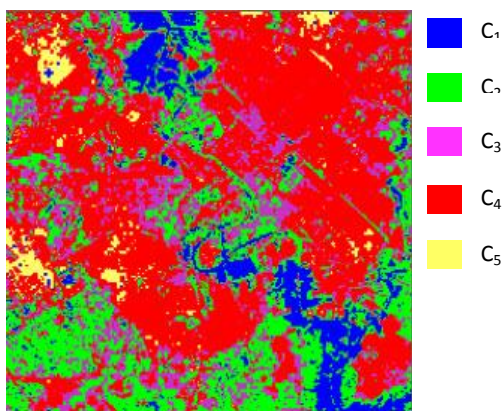


Figure (9) Classified image using results of K-means.

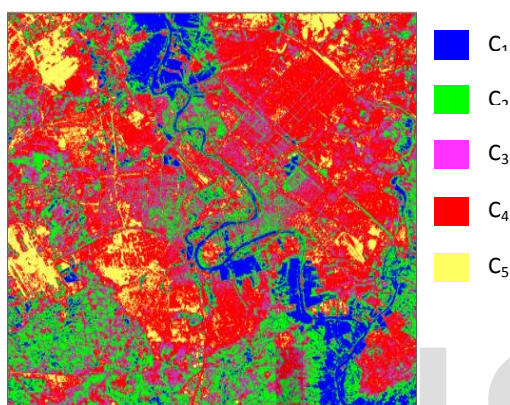


Figure (10) Classified image using pixel based method.

standard classified image given by GSC. Moreover, this relation can be employed to estimate the accuracy of each class in the image separately. This is carried out by examining pixels of classified image that identify same class in the standard classified image, which can be given in the following relation:

$$P_k = \frac{C_c}{T_k} \times 100\% \quad \dots (19)$$

Where, P_k is the classification accuracy of k^{th} class that represents the user's accuracy (UA), C_c is the total number of pixels that classified as same as its corresponding pixels in the standard classified image, and T_k is the total number of pixels belong to the k^{th} class in the classified image.

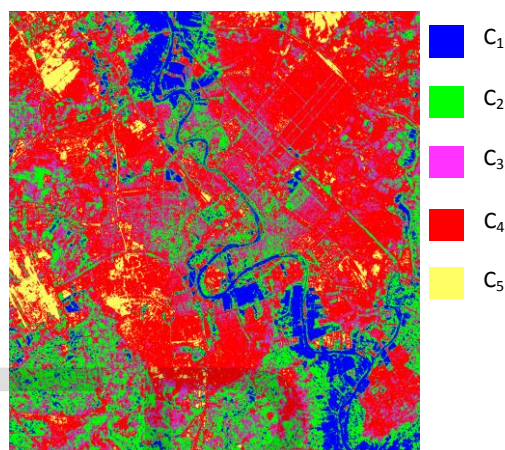


Figure (11) Considered image classified by GSC.

7.1. Results Evaluation

The result of the pixel based method is shown more descriptive than that of the block based method, since the pixel based method was able to sense the small variation found in some image regions, and classify the fine details in that regions. Such that, the result of the pixel based method is only adopted to be evaluated. To estimate the results accuracy of this method, a standard image was classified by Geological Surveying Corporation (GSC) is used for the purpose of comparison with the result. This standard image is classified by Maximum Likelihood Method using ArcGIS software version 9.3. The classification map in this image is shown in Figure (11). The process of the comparison was carried out pixel by pixel to guarantee the comparison result gave more realistic indication. The procedure is done by counting the number of pixels in the classified image that identifying same class in the standard classified image. Then, the evaluation percent (P_T) of the identical classified pixels (C_p) to the total number of pixels (T_p) found in the image is computed by the following relation:

$$P_T = \frac{C_p}{T_p} \times 100\% \quad \dots (18)$$

Where, P_T represents the overall accuracy (OA) of the proposed classification relative to the classification of the

Accordingly, the producer accuracy (PA) can be computed using the following relation:

$$P_p = \frac{C_c}{C_p} \times 100\% \quad \dots (20)$$

Where, P_p represents the producer accuracy (PA), and C_p is the total number of pixels of each class in the standard classified image. The evaluation results of the pixel based gave an overall accuracy P_k of about 93%, whereas class accuracy is listed in Table (3) for the five classes found in the image.

Table (3) Resulted producer accuracy.

Class	P_p
C1	97%
C2	94%
C3	91%
C4	93%
C5	90%

These results showed the classification method was successful due to the percents of identical classes (P_k) were acceptable. It is noticeable that the class of Open Land (C_5) has less identical percent due to it was appeared very bright region in the used image, while the other classes have a high identical percent. The high classification scores ensure the ability of the proposed

method to make accurate classification since it uses an efficient image segmentation method and depends on optimizing effective descriptive features. The fractal technique appears well suited to analyze textural features in remotely sensed images, as the environmental features captured in the image are often complex and fragmented. In general, the proposed classification method was successfully indicating actual results to classify satellite images, which ensure the efficiency of the employed method and the good performance of the classification.

8. CONCLUSION

Hybrid segmentation method is an efficient method to make spectrally homogenous image blocks and fractal geometry provides a suitable satellite image classification where, the fractal features are estimated for each block to determine the image classes that stored as comparable models in dataset dictionary. The results pixel by pixel classification method was successful due to the percents of identical classes (P_k) were acceptable. It is noticeable that the class of Open Land (C_3) has less identical percent due to it was appeared very bright region in the used image, while the other classes have a high identical percent. The classification results are found identifying the actual training data, which ensure the success of the proposed method and the effective performance of the classification.

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