K-Means Based SVD for Multiband Satellite Image Classification

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Abstract— The motivation we address in this paper is to classify satellite image using the singular value decomposition (SVD) technique, the proposed method is consisted of two phases; the enrollment and classification. The enrollment phase aims to extract the image classes to be stored in dataset as a training data. Since the SVD method is supervised method, it cannot enroll the intended dataset, instead, the moment based K-means was used to build the dataset. The enrollment phase showed that the image contains five distinct classes, they are; water, vegetation, residential without vegetation, residential with vegetation, and open land. The classification phase consisted of multi stages; image composition, image transform, image partitioning, feature extraction, and then image classification. The classification method used the dataset to estimate the classification feature SVD and compute the similarity measure for each block in the image. The results assessment was carried out by comparing the results with a reference classified image achieved by Iraqi Geological Surveying Corporation (GSC). The comparison process is done pixel by pixel for whole the considered image and computing some evaluation measurements. It was found that the classification method was high quality performed and the results showed acceptable classification scores of about 70.64%, and it is possible to be approaches 81.833% when considering both classes: residential without vegetation and residential with vegetation as one class for SVD method.

Keywords — Satellite image, Image classification, segmentation, SIC, KMeans, SVD, Moment.

1. Introduction

Remote sensing uses satellite imagery technology to sense the landcover of Earth. At the early of 21st century, satellite imagery became widely available with affordable [1]. Satellite image classification is the most significant technique used in remote sensing for the computerized study and pattern recognition of satellite information, which is based on diversity structures of the image that involving rigorous validation of the training samples depending on the used classification algorithm [2]. It is an extreme part of remote sensing that depends originally on the image resolution, which is the most important quality factor in images [3]. Image Classification or segmentation is a partitioning of an image into sections or regions. These regions may be later associated with ground cover type or land use, but the segmentation process simply gives generic labels (region 1, region 2, etc.) to each region. The regions consist of groupings of multispectral or hyperspectral image pixels that have similar data feature values. These data feature values may be the multispectral or hyperspectral data values and/or they may be derived features such as band ratios or textural features [4]. The powerful of such algorithms is depends on the way of extracting the information from huge number of data found in images. Then, according to these information, pixels are grouping into meaningful classes that enable to interpret, mining, and studying various types of regions that included in the image [3]. Many applications based on using Landsat imagery in a quantitative fashion require classification of image pixels into a number of relevant categories or distinguishable classes [5]. These applications use image classification as an important tool used to identify and detect most relevant information in satellite images [6]. Bin and et.al [7] provide a neural network-based cloud classification using the wavelet transforms (WT) and singular value decomposition (SVD) to extract the salient textural feature of the data. Mayank [4] provide a feed-forward neural network for satellite image segmentation, which provides a way to solve the problem of parametric-dependence involved in statistical approaches using a robust, fault-tolerant, feed-forward neural network. Márcio and et al., [8] presented a methodology for the landcover classification of satellite images based on clustering of the Kohonen’s self-organizing map (SOM). Sathya and Malathi [9] established a segmentation and classification of remote sensing images. This classified image is given to KMeans algorithm and Back Propagation algorithm of ANN to calculate the density count, the excremental result found that K-means algorithm gives very high accuracy, but it is useful for single database at a time. Rowayda [10] Performed an experimental survey for the SVD as an efficient transform in image processing applications, some contributions that were originated from SVD properties analysis in different image processing are proposed. Bjorn Y. [11] established method for the classification of satellite images into multiple predefined landcover classes. Ankayarkanni and Ezil [12] proposed an efficient image classification technique for satellite images with the aid of KFCM and artificial neural network (NN). Ankayarkanni B. and et al. Harikrishnan and Poongodi S. [13] implemented a cellular with fuzzy rules for classifying the satellite image and analyzed the quality of classified image. Akkacha and et al [14] proposed a combination of three classification methods which are K-means, LVQ (linear vector quantization) and SVM (support vector machine). Thwe and et al [15] proposed a method for area classification of Landsat7 satellite image. The paper is structured as follows. Section 2 describes the contribution of work. In Section 3 describes theoretical frame work. In Section 4 describe the proposed SIC. Finally, section 5 describes the results and discussion.

2. Contribution

The proposed method is based on the use of k-means based singular value decomposition (SVD) for satellite image classification. The use of such method enables to study the concepts that concerned with training phase. The study of training phase capabilities leads to improve the classification results. SVD is stand for supervised method depending on predefined dataset stored in the dictionary that firstly established using the k-means. The optimal run of training phase leads to create optimal dataset stored in the dictionary and then used to determine intended classification results when the classification phase is running. Implies, the optimal choice of the dataset indicates an optimal classification results.

3. Theatrical Basis

Classification of satellite images can be achieved by unsupervised or supervised procedures, it is performed when the image needs to be assigned into a predefined classes based on a number of observed attributes related to that image. This refers to the task of extracting information from satellite image; the information is assigned into classes according to specific features that distributed in the image [16]. The following sections introduce the concepts of the used features: singular value decomposition (SVD) and moment besides the clustering based on K-Means.

3.1 Singular Value Decomposition

Singular Value Decomposition (SVD) is a mathematical tool widely in image classification; it is useful factorizations method in linear algebra [17]. SVD technique is based on a theorem of linear algebra that mentions; a rectangular $m\times n$ matrix A having m rows and n columns in which $m\geqslant n$, is can be broken down into the product of three matrices, as given in Equation (1) [18].

$$A=USV^{\mathbf{T}} \quad \dots (1)$$

Where U is a $m\times n$ matrix of the orthonormal eigenvectors of AA^T called the left singular vectors of A satisfy equation (2), V^T is the transpose of a $n\times n$ matrix containing the orthonormal eigenvectors of $A^{\boldsymbol{T}}A$ called the right singular vectors of A satisfy equation (3), $I_{n\times n}$ and $I_{p\times p}$ are the identity matrices of size n and p, respectively, and S is a $n\times n$ diagonal matrix with nonnegative diagonal entries of the singular values which are the square roots of the eigenvalues of $A^{\boldsymbol{T}}A$ and called the singular values of A, which given in eq.(4) [19], as follows:

$$U^{\mathbf{T}}U=I_{n\times n} \quad \dots (2)$$

$$V^{\mathbf{T}}V=I_{p\times p} \quad \dots (3)$$

$$S=\begin{bmatrix} \sigma_1 & 0 & \cdot & 0 & 0 \\ 0 & \sigma_2 & \cdot & 0 & 0 \\ 0 & 0 & \cdot & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & . & \sigma_{n-1} & 0 \\ 0 & 0 & . & 0 & \sigma_n \end{bmatrix} \quad \dots (4)$$

Where $\sigma_1 \geq \sigma_2 \geq \cdot\cdot\cdot \geq \sigma_p$, $p = \min\{m, n\}$, and $U = [u_1 \ \dots \ u_m]$, $V = [v_1 \ \dots \ v_n]$. In such case, the SVD value is the minimum value of diagonal terms, which can be used as a distinguished feature for any image segment.

3.2 K-Means Based Clustering

K-means is one of the effective unsupervised learning methods that solve the clustering problem. The application of this algorithm on digital image requires being starts with some clusters of pixels in the feature space, each of them defined by its center. The first step is randomly choosing a predefined number of clusters. Second step is allocating each pixel to the nearest cluster. While, the third step is computing new centers with new clusters. These three steps are repeated until convergence. Therefore, the k-means algorithm adopts the following three steps till reaching the final state [9].

1. Determine the centroid coordinate.
2. Determine the distance of each object to the centroid.
3. Group the object based on minimum distance.

3.3 Moment Based Classification

The concept of moment is derived from Archimedes' discovery of the operating principle of the lever. In the lever one applies a force, in his day most often human muscle, to an arm, a beam of some sort. Archimedes noted that the amount of force applied to the object (i.e., moment) is defined as the following equation:

$$M = r^s \times F \quad \dots (5)$$

Where F is the applied force, and r is the distance from the applied force to object and s is the order of the moment. In image processing, the pixel value represents the force F, whereas r is the distance between the pixel and the center of the moment. The moment gives an actual indication about the contents of an image or image segment, such that it is used to distinguish different image segment from each other. Also, it is used to describe details of small areas found in the image, which is a useful for image classification [20].

4. Proposed Classification Method

The generic structure of the proposed method for satellite image classification using K-means based SVD is shown in Figure (1). It is shown that the proposed method is designed to be consisted of two phases: enrollment and classification. The enrollment phase goes to collect the training dataset (referred as *A*), which an offline phase is responsible on collecting sample image classes to be stored in dataset matrix to be a comparable models. Whereas the classification phase is an online phase responsible on verifying the contents of the test image in comparison with the trained models found in the dataset, this phase depends on the dataset created by the enrollment phase. Both phases are composed of the three preprocessing stages include: image composition, image transform and preparing. Then, the enrollment includes sequenced stages of image partitioning, feature extraction and then clustering to establish the dataset. On the other hand, the classification phase consist of sequenced stages aims to extract the classification features from the employed image unit. In addition, there are an intermediate stages included in the classification are used to achieve the intended purpose are shown in Figure (1) and described in the following sections.

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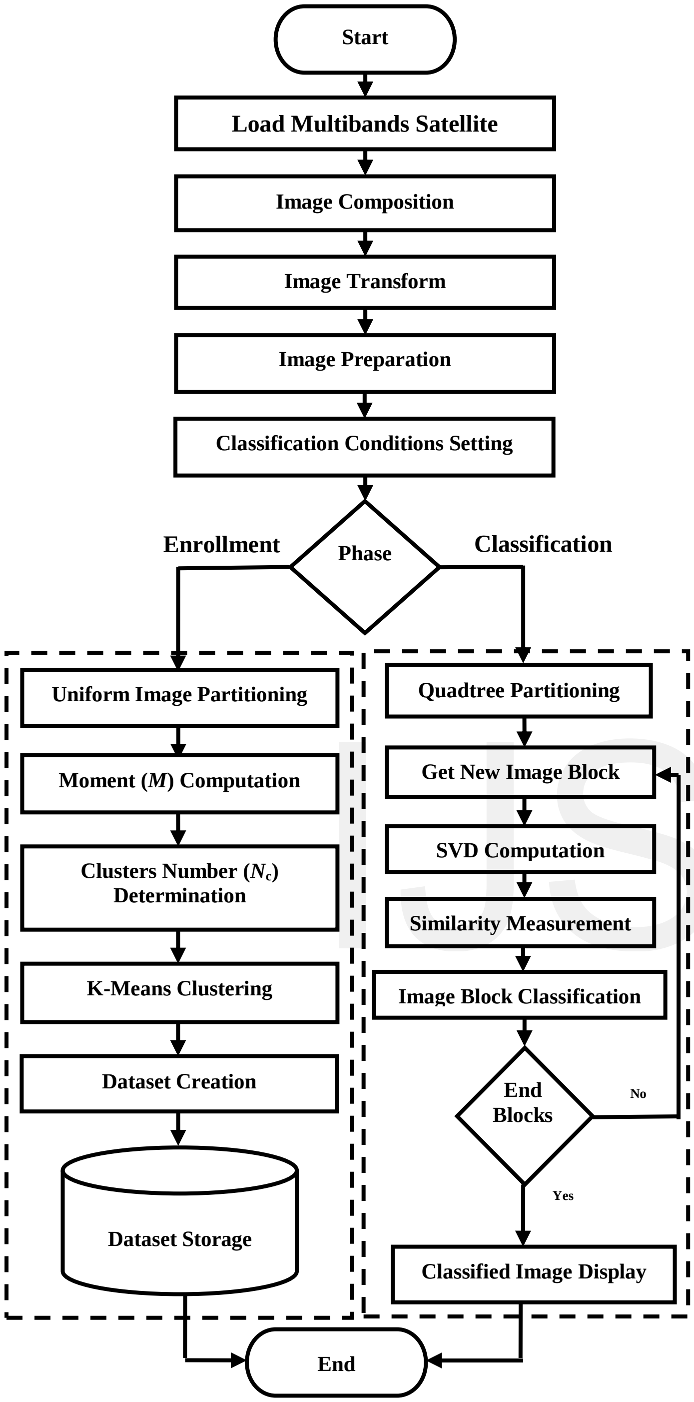

Figure (1) Block diagram of the proposed SIC method.

4.1 Image Composition

Satellite image is usually taken in multibands; this stage is aiming to compose the most informatic three bands in one color image given in RGB color space. The dispersion coefficient (D) of the whole image $f(i,j)$ that given in equation (6) is used as a measure for quantifying whether a set of observed details are clustered or dispersed compared to a standard case. This parameter indicates the amount of the information found in each band. The three bands of greatest value of D are chosen to be combined with each other to make the composed image $F_{R,G,B}(i, j)$ employed in the following stages.

$$D_k = \frac{\sigma^2}{\mu} \qquad \text{... (6)}$$

Where, μ and σ^2 are the mean and variance of k^{th} band of satellite image of $W \times H$ resolution as given in equations (7 and 8). Such that, the green band F_G, red band F_R, and blue band F_B are assumed to be the first three bands that possess maximum dispersion coefficient D_k as given in equations (9-11):

$$\mu = \frac{1}{W \times H} \sum_{i=0}^{W-1} \sum_{j=0}^{H-1} f_{ij} \qquad \text{... (7)}$$

$$\sigma^2 = \frac{1}{W \times H} \sum_{i=0}^{W-1} \sum_{j=0}^{H-1} \left(f_{ij} - \mu\right)^2 \qquad \text{... (8)}$$

$$F_G(i,j) = \mathrm{Max}_{\mathrm{First}}(D_k) \qquad \text{... (9)}$$

$$F_R(i,j) = \mathrm{Max}_{\mathrm{Second}}(D_k) \qquad \text{... (10)}$$

$$F_B(i,j) = \mathrm{Max}_{\mathrm{Third}}(D_k) \qquad \text{... (11)}$$

4.2 Image Transform

The three estimated bands F_R, F_G, and F_B are converted into newly bands according to *YIQ* color transformation system. The *Y* represents the intensity band, whereas both *I* and *Q* represent the chrominance bands. Just the *Y* band is useful in the present work, which can be noted as F_T and estimated according to the following relation:

$$F_T(i,j)=0.2989\, F_R(i,j)+0.5870\, F_G(i,j)+0.1140 F_B(i,j) \qquad \text{... (12)}$$

4.3 Image Preparation

This stage is regarded to increase the contrast of the given material 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:

$$F_P = aF_T + b \qquad \text{... (13)}$$

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.

$$a = \frac{Max_2 - Min_2}{Max_1 - Min_1} \qquad \text{... (14)}$$

$$b = \frac{Max_2 \times Min_1 - Max_1 \times Min_2}{Max_1 - Min_1} \qquad \text{... (15)}$$

4.4 Classification Conditions Setting

In this stage, the intended conditions of classification status are determined. This conditions are used in both enrollment and classification phases. For the partitioning stage, the maximum block size (B_{Max}) and minimum block size (B_{Min}) are set at the situation that gave best classification

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results. This depends on the number of try making for achieving best results.

4.5 Enrollment Phase

The enrollment of dataset is an important step in the image classification. It is used for determining the image classes depending on sequenced stages. It is intended to uniformly partition the prepared image (F_P) into equal blocks of size B_{Max}. The reason of using B_{Max} is to make the dataset containing greater number of information related to each class, and make the moment is the feature that recognizes each part. K-Means algorithm is used for grouping these features and then determining the best clusters (centroids) within the resulted features. The image part belongs or closes to each centroid are stored in dataset array to be used in the classification phase. This dataset can resized and scaled down to be half or quarter B_{Max} as needed in the classification. The average of the two successive elements gave new value in the half scaled down dataset, and another averaging leads to get quarter scaled down for the dataset. The Moment is a specific quantitative measure used to represent the information found in each image block. The shape of a set of pixels is a distribution of mass, which can be described by first-ordered moment given in equation (5), where the applied force (F_P) represented the pixel of block and r is the distance from the applied force to the center of block. In such case, the pixel value (F_P) is regarded as the meant force, while the distance (D_s) is determined depends on the position of each pixel (In first, second, third, or fourth quarters) as shown in Figure (2). The moment of each block can be determined as shown below:

1. Compute the Euclidean distance D_s between each pixel of a specific block and the center of that block (the difference between the pixel and the center of block) as follows:
   a. If the pixel $F_P(i, j)$ falls in the First quarter then the D_{s1} is computed by using the following relation:

   $$D_{s1} = \sqrt{(|i - i_o| - 0.5)^2 + (|j - j_o| - 0.5)^2} \quad \text{... (16)}$$

   b. If the pixel $F_P(i, j)$ falls in the Second quarter then the D_{s2} is computed by using the following relation:

   $$D_{s2} = \sqrt{(|i - i_o| - 0.5)^2 + (|j - j_o| + 0.5)^2} \quad \text{... (17)}$$

   c. If the pixel $F_P(i, j)$ falls in the Third quarter then the D_{s3} is computed by using the following relation:

   $$D_{s3} = \sqrt{(|i - i_o| + 0.5)^2 + (|j - j_o| - 0.5)^2} \quad \text{... (18)}$$

   d. If the pixel $F_P(i, j)$ falls in the Fourth quarter then the D_{s4} is computed by using the following relation:

   $$D_{s4} = \sqrt{(|i - i_o| + 0.5)^2 + (|j - j_o| + 0.5)^2} \quad \text{... (19)}$$

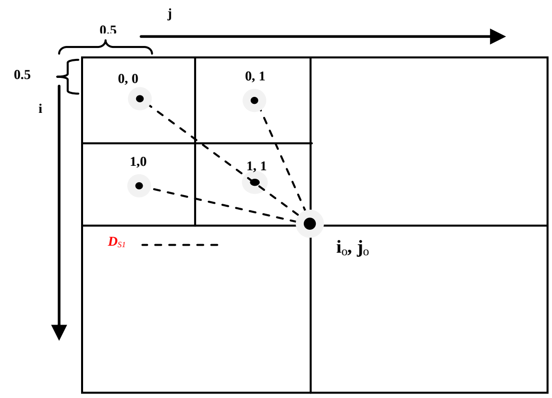
   Where i_0, j_0 are represent the indices of the center block.
2. Compute the moment M_p (i, j) of each pixel in a specific block of image by using the following relations:

   $$M_p\,(i, j) = F_P\,(i, j) \times D_s \quad \text{... (20)}$$

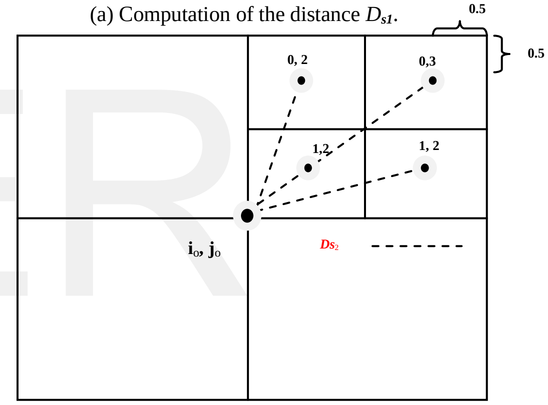
3. Compute the moment of a specific block (M) in image by using the following relation:

$$M = \frac{1}{B_h \text{x} B_w} \sum_{i=0}^{B_h} \sum_{j=0}^{B_w} M_p(i, j) \quad \text{... (21)}$$

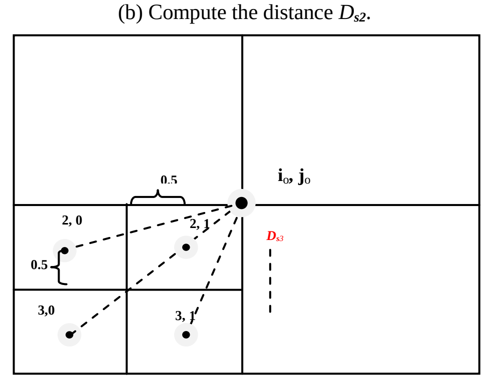
Where B_h *is* the height of block and B_w is the width of block, M (i, j) represent the moment of pixel in a specific block of image, and F_P (i,j) represent the pixel value of a specific block at position (i,j), i, and j are indices of the pixel in block of image.



(a) Computation of the distance D_{s1}.



(b) Compute the distance D_{s2}.



(c) Compute the distance D_{s3}.

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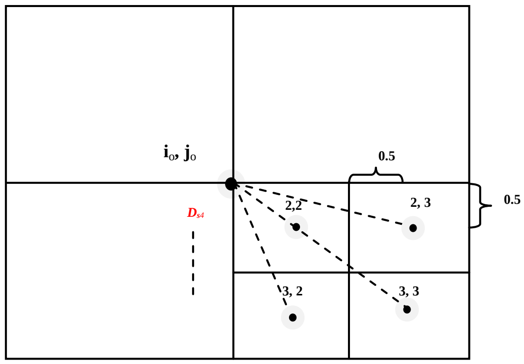

(d) Compute the distance D_{s4}.

Figure (2) The distance D_S computation.

The implementation of K-Means depends on two input parameters, they are; the number of clusters (or classes) and the moment values of each block in the image. Actually, the number of classes (N_C) in the prepared image is determined in the following steps:

1. Determine the number of pixels in satellite image $\boldsymbol{N_T}$ by using the following relation:

   $$\boldsymbol{N_T} = W \times H \quad \dots (22)$$

   Where W represents the width of satellite image and H represents the height of satellite image.
2. Determine the standard deviation ($\boldsymbol{\sigma}$) to prepare image that is by employing equation (8) to be modified in the following form:

   $$\boldsymbol{\sigma} = \sqrt{\frac{1}{N_T}\sum_{i=0}^{W-1}\sum_{j=0}^{H-1}(F_P\ (i,j) - \overline{F_P})^2} \quad \dots (23)$$

   Where $\overline{F_P}$ is the mean of the prepared image that can be computed by the following relation:

   $$\overline{F_P} = \frac{1}{N_T}\sum_{i=0}^{W-1}\sum_{j=0}^{H-1} F_P(i,j) \quad \dots (24)$$
3. Calculate the number of pixels $\boldsymbol{N}$ in the image that fall within the range of $2\boldsymbol{\sigma}$ in the image distribution.
4. Compute the percent (P) of the pixels number (N) in $2\boldsymbol{\sigma}$ expansion and the number of pixels in whole image ($\boldsymbol{N_T}$) by using the following relation:

   $$P = \frac{N}{N_T} \quad \dots (25)$$
5. The number of classes ($\boldsymbol{N_C}$) is equal to the multiplication of the percent (P) by the maximum probable number (P_M) of classes may found in the satellite images, as follows:

   $$\boldsymbol{N_C} = P \times P_M \quad \dots (26)$$

Dataset Formatting and Storing deals with output centroid of K-Means algorithm. The image block corresponding or closest to centroid moment is stored in two dimensional dataset array (A), in which each block is converted into one dimensional vector to be one column in A. Such that, the width of A is the number of classes (N_c) while the height of A is equal to the number of pixels found in the block (i.e., $B_{Max} \times B_{Max}$).

4.6 Classification Phase

The classification phase is carried out after performing the training phase (enrollment). It can be achieved by using SVD method depends on the established dataset array A, where the classification phase used the quadtree to segment the prepared image into non uniform blocks restricted between B_{Max} and B_{Min}. Then each square either leaved as it or subdivided into four quadrants when it satisfies the partitioning conditions. Then, each block is assigned to the dataset array A to compute the classification feature. According to this feature, the block is labeled with available classes. Since the SVD classification method needs to partition the image into predefine sized image block, quadtree partitioning method is used for segmenting the image into addressed image blocks. Therefore, the implementation of quadtree partitioning method requires to set some parameters are related the partitioning conditions, which are used to control the process of partitioning. These control parameters are given in the following:

1. Maximum block size ($\boldsymbol{B_{max}}$).
2. Minimum block size ($\boldsymbol{B_{min}}$).
3. Mean factor ($\boldsymbol{\beta}$): represents the multiplication factor; when it is multiplied by global mean ($\boldsymbol{M_g}$) it will define the value of the extended mean ($\boldsymbol{M_e}$), i.e. $\boldsymbol{M_e} = \boldsymbol{\beta} \times \boldsymbol{M_g}$.
4. Inclusion factor ($\boldsymbol{\alpha}$): represents the multiple factor, when it is multiplied by the global standard deviation ($\boldsymbol{\sigma}$) it will define the value of the extended standard deviation ($\boldsymbol{\sigma}$), i.e. $\boldsymbol{\sigma}_e = \boldsymbol{\alpha} \times \boldsymbol{\sigma}$.
5. Acceptance ratio ($\boldsymbol{R}$): 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.

The adopted SVD feature is estimated for each block to be compared with that of the dataset A. This is first including the conversion of the block into one dimensional vector (V) and included in the dataset array A to be the sixth column, such that the array will dimensioned as $[(N_c+1) \times (B_{Max} \times B_{Max})]$. . The challenged problem is to fit the length of columns of the dataset array A with the vector V. This problem is over comes by down sampling the length of columns of A to be equal to the length of the vector V. The down sampling of each column elements is done by averaging process, in which the reducing ratio (R) is computed by dividing the length of current image block B_L by the length of the A columns (i.e., $B_{Max} \times B_{Max}$) as follows:

$$R = \frac{B_L}{B_{Max} \times B_{Max}} \quad \dots (27)$$

When the columns of the dataset array A are fitted, the *SVD* feature of current image block can be computed in comparison with dataset columns.

The differences between the computed SVD are used to compute the similarity measure (S_{V_K}) for the last column with that of its previous columns as follows:

$$S_{V_K} = 1 - \left|SVD_{N_{c+1}} - SVD_i\right| \quad \dots (28)$$

Where, SVD_k is the computed singular value decomposition feature of the k[th] class, and SVD_{k+1} is the singular value decomposition of the image block that need to be classified. The maximum value of S_{V_K} refers to the class that image block is belonging to. The comparison leads to classify the image blocks.

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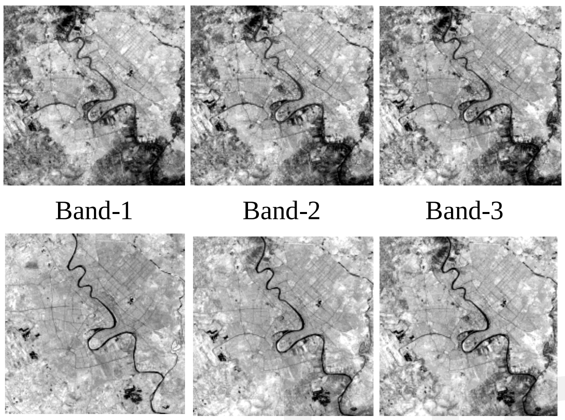
5. RESULTS AND DISCUSSION

The multiband satellite image used in the classification was capture by Landsat satellite, it cover the area of Baghdad city in Iraq. Figure (3) shows the six bands of used satellite image. The resolution of each band is *1024x1024 pixels,* which carried acceptable range of informatic details about the image of consideration. 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.



Band-4 Band-5 Band-6

Figure (3) The used six bands of Baghdad city given by Landsat.

The results of the dispersion coefficient (*D*) of used six bands are given in Table (1). It is shown that the greatest three values of the dispersion coefficients are belong to the bands (1, 2, and 3) respectively. Therefore, to compose these bands with each other for making one color image, it is assumed that the band (1) is stand for green (*G*), band (2) is stand for red (*R*), and band (3) is stand for blue (*B*) in the RGB colored image. Figure (4) shows the result of the composition process. Actually, the composed image enjoyed with more contrast and more visual details.

Table (1) Resulted dispersion coefficient of the adopted six bands.

Band	*D*
1	0.411398
2	0.402812
3	0.390436
4	0.259853
5	0.27828
6	0.319443

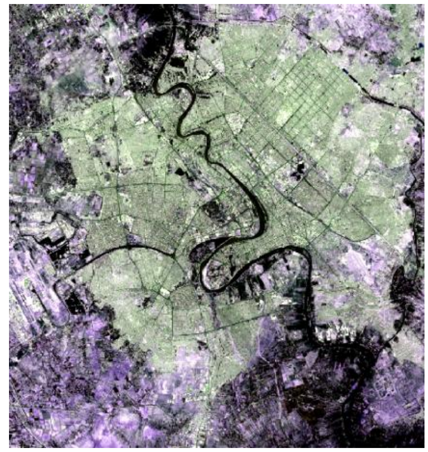


Figure (4) Result of the image composition.

Image transform is used to enhance the satellite image by using equation (12). It is applied on the three color components (*R*, *G*, and *B*) of the image, which leads to converting the image from three bands into one band is better and suited for machine based analysis. The image preparation aimed to make the contrast of the considered image is full. Full contrast is achieved when choosing the values of Min_2 and Max_2 to be 0-255 by using equation (13). Figure (5) shows the result of transformed and prepared image.

Figure (5) Results of image transform and preparation.

5.1 Enrollment Results

The result of enrollment phase is a dataset stored in two dimensional array (*A*), the number of columns of this array is equal to the number of classes, while the number of rows of this array is equal to the length of the class. The length of the class is equal to the number of pixels contained in the image block, which can be determined by product the width by height of the block. The results of the uniform image partitioning is shown in Figure (6), in which the prepared image of resolution 1024×1024 *pixel* is partitioned into image blocks each of size 8×8 *pixel*. The blocks greater than B_{Max} lead to confuse the classification results, whereas the blocks less than B_{Min} lead to

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poor image parts and no information may found in image blocks. The moment of each image block was computed according to equation (21), the minimum and maximum resulted values of computed moment are shown in Figure (7). It is noticeable that the minimum value of the moment is zero, while the maximum value is 808.9465. The zero value refers to empty blocks, which have no information in, while the maximum value refers to much information found in that block. The application of the K-Means needs to set the range of expanding the clusters along the moment scale. Therefore, the range between the maximum and minimum values of the moment is 808.9465, which is divided into five (N_{C}=5) of regions each of which extended by a maximum distance is equal to (D_k=808.9465/5=161.7893 *unit*).

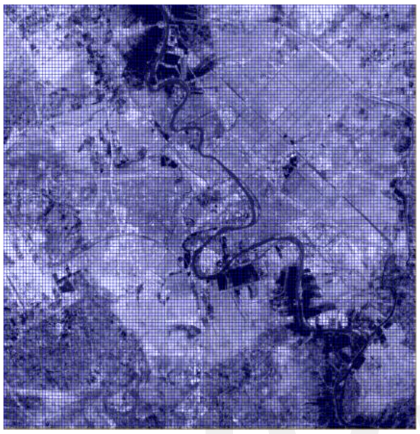

Figure (6) Result of uniform image partitioning (B_{Max}=8 *pixels*).

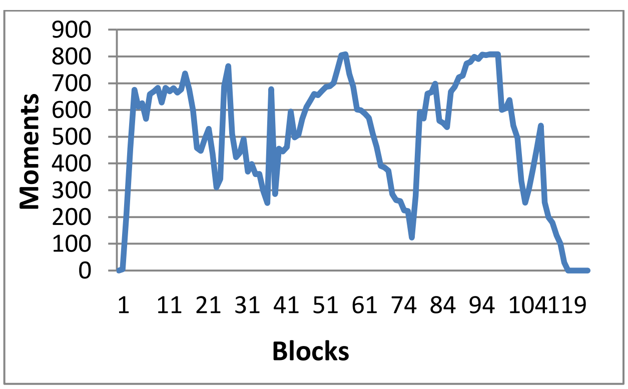

Figure (7) Sample range of resulted moment values.

Finally, the dataset array *A* contains image blocks corresponding to the final centroids resulted from the application of the K-Means, each of these blocks represents a one column in the dataset array *A* sequentially. Figure (8) shows the behavior of these five columns that represent the labels of the discovered five classes of the image under consideration, whereas Figure (9) displays the position of the image blocks that consisting in the dataset array *A*. 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 an equivalent distances in the grey scale depending on the details of each class.

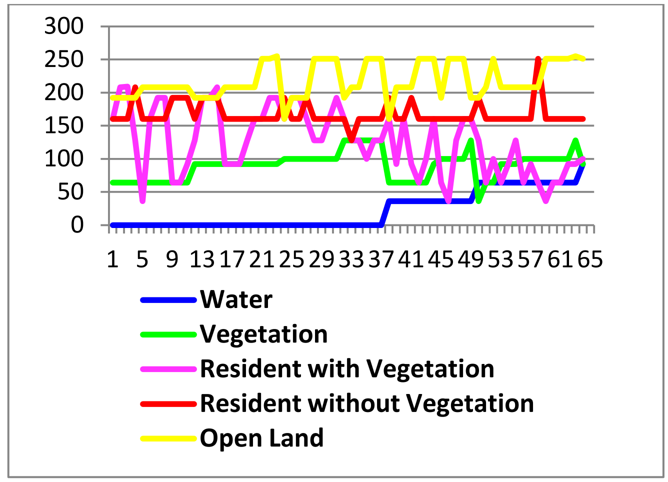

Figure (8) Behavior of five columns of five classes in the image.

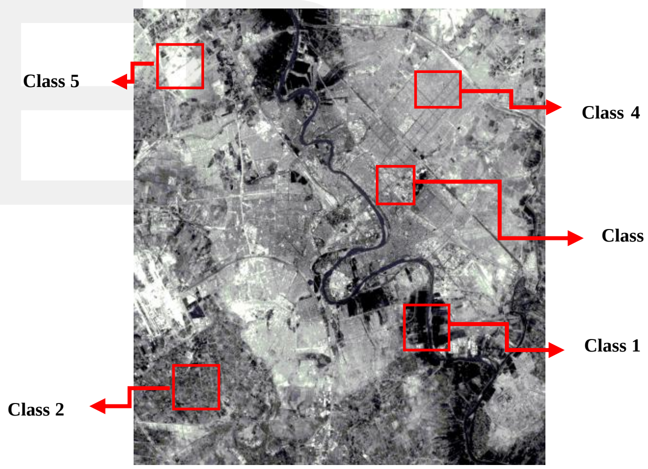

Figure (9) Resulted five classes.

5.2 Classification Results

In the SVD method, the finding of best values of control parameters and the best partitioning of the quadtree is very important problem since the control parameters govern the partitioning process that lead to intended classification. Figure (10) shows the best control parameters of quadtree partitioning method.

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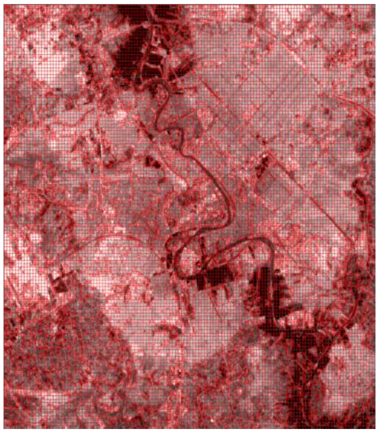

Maximum block size=8

Minimum block size=2

Acceptance ratio =0.2

Inclusion factor = 0.6

Threshold =0.6

Figure (10) Result of quadtree partitioning for control parameters.

The classification result of the prepared image using the SVD method is displayed in Figure (11). It is shown that the distribution of classes along the image region was acceptable. The best values of control parameters make the partitioning process more accurate, which leads to accurate classification results. It seen that the results of image partitioning based on image homogeneity measurements are very acceptable. The result of the partitioning depends on the quantity of the uniformity for each block.

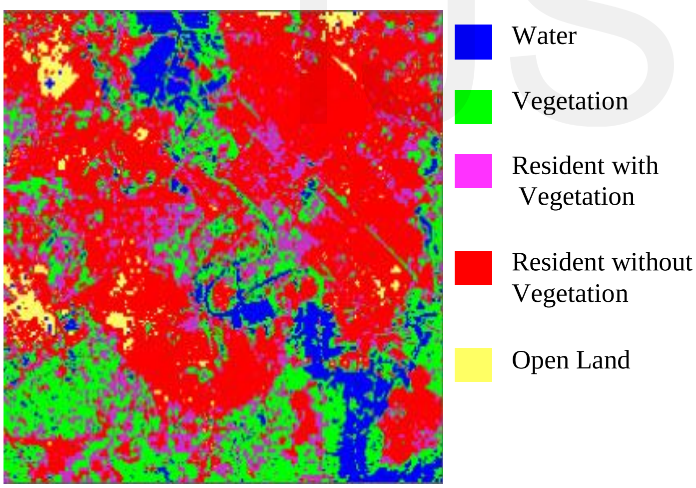

Figure (11) Classified image using SVD method.

To estimate the accuracy of the proposed two methods of satellite image classification, a standard image is classified by Geological Surveying Corporation (GSC) used for purpose of comparison. 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 (12), there are five distinct classes; there are five distinct classes; they are: water, vegetation, residential with vegetation (Resident -1), residential without vegetation (Resident -2), and open land, let we denote them as $\boldsymbol{C_1}$ for class water and $\boldsymbol{C_2}$ for class vegetation and $\boldsymbol{C_3}$, $\boldsymbol{C_4}$, $\boldsymbol{C_5}$ for classes Resident with vegetation, Resident without vegetation, and Open Land respectively.

The process of 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 gave identify same class in the standard classified image. Then, the percent (P_T) of the identical classified pixels (C_p) to the total number of pixels (T_p) found in the image is computed as follows:

$$P_T = \frac{C_p}{T_p} \times 100\% \qquad \ldots (29)$$

Where, $\boldsymbol{P_T}$ represents the overall accuracy (OA) of the proposed classification relative to the classification of the 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:

$$P_k = \frac{C_c}{T_k} \times 100\% \qquad \ldots (30)$$

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

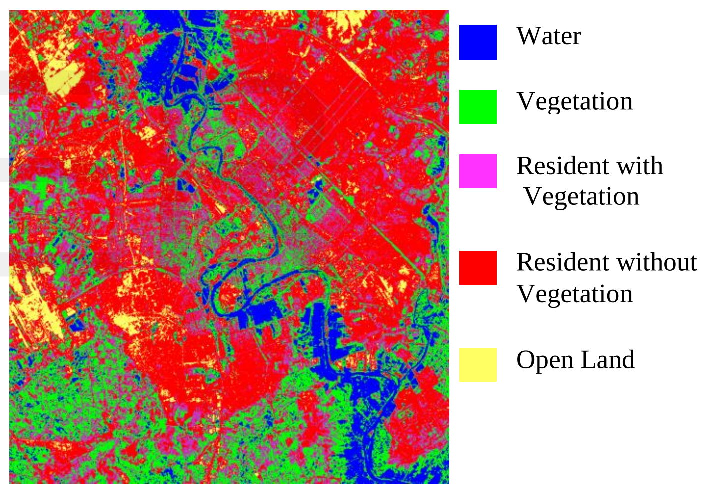

Figure (12) The Standard satellite image classification given by GSC.

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

$$P_p = \frac{C_c}{C_p}\ x\ 100\% \qquad \ldots (31)$$

Where, $\boldsymbol{P_p}$ represents the producer accuracy (PA), and $\boldsymbol{C_p}$ is the total number of pixels of each class in the standard classified image. The two parameters $\boldsymbol{P_c}$ and $\boldsymbol{P_p}$ are prepared to estimate both the commission error ($\boldsymbol{E_C}$) and omission error ($\boldsymbol{E_O}$) as follows:

$$E_C = 100 - P_K \qquad \ldots (32)$$

$$E_O = 100 - P_P \qquad \ldots (33)$$

The use of equation (29) on the whole image gives best estimation for pixel classification rather than the use of random selected areas since the selection of small considered area may gave unstable result at each run of comparison due to the change of position of considered area. The evaluation results

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SVD method is listed in Table (2), this table includes the overall accuracy and class accuracy for the SVD classification method.

These results showed the SVD classification method was successful due to the percents of identical classes (P_k) were acceptable. It is noticeable that the class of Resident with Vegetation (Resident -1) has less identical percent due to the details of such class is large enough to be described in the used image, while the class of water has a high identical percent due to it appeared in different spectral intensity in comparison with other classes, whereas; other classes are distributed moderately between the two mentioned classes. Also, it showed that the overall accuracy of the classified satellite image is *70.64075%*, while the total accuracy is about *81.83279%* when the Resident without Vegetation (Resident -2) and Resident with vegetation (Resident -1) classes are regarded as same class. Figure (13) indicates that the class of Water showed high identification percent in comparison with that of standard image relative to other classes in the standard image. Moreover, Table (2) mentioned that the largest user's accuracy achieved with the high accuracy for the class of water, the high value of user's accuracy has been found *81.13046 %* for comparison between the results of the standard classified image and the SVD based classified image, while the smallest user's accuracy was found in the class of Resident with Vegetation *49.34067%*. It is concluded that the rest user's accuracy for the classes of satellite image are limited between the maximum and minimum percent user's accuracy. On other hand, the high producer accuracy achieved for the class Resident without Vegetation is *86.53535%* and the smallest producer accuracy for the class Resident with Vegetation is *43.20286%* the rest classes are limited between the larger and smaller producer accuracy as shown in Figure (14), where the class of Resident with Vegetation has the smallest accuracy value. Also, Figure (15) describes the variation of each class in both user's accuracy and producer accuracy, where the user's accuracy classes: water, resident With Vegetation, and Open Land class are greater than their producer accuracy, while the user's accuracy of Vegetation and Resident Without Vegetation are less than the producer accuracy of the standard classified image, which indicates the classes of water, Resident with vegetation and, Vegetation are more changed compared with the other classes.

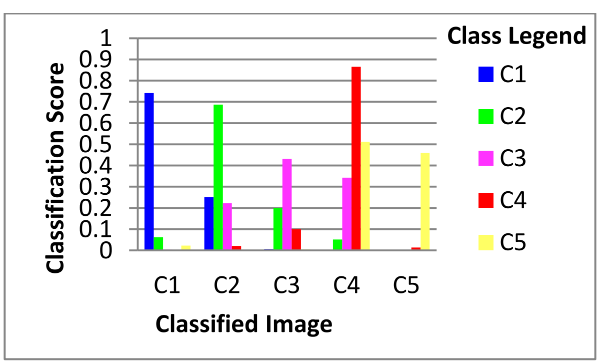

Figure (13) Classes accuracy in SVD method.

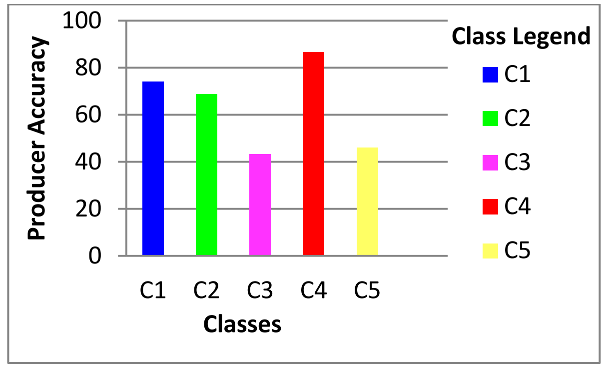

Figure (14) Producer accuracy of classes in SVD method.

Table (2) The results of SVD classification method.

		Standard Classified Image					C_T	P_K	E_C
		C_1	C_2	C_3	C_4	C_5			
Classified Image	C_1	71265	14697	554	108	1216	87840	81.13046	18.87
	C_2	24023	161395	46607	9504	83	241612	66.79925	33.201
	C_3	665	46725	90637	45410	259	183696	49.34076	50.659
	C_4	136	12025	71947	392520	27776	504404	77.81857	22.182
	C_5	0.0	17	49	6053	24905	31024	80.27656	19.724
C_P		96089	234859	209794	453595	54239	1048576		
P_p		74.1656	68.71996	43.20286	86.53535	45.917			
E_O		25.83438	31.28004	56.79714	13.46465	54.083			
OA		**70.64075**							

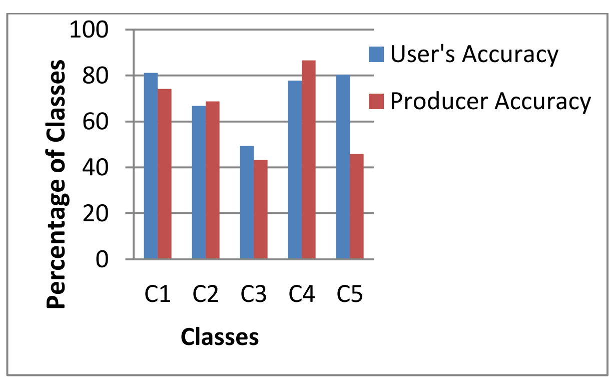

Figure (15) Relation between producer and user's accuracy of classes By using SVD Method.

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6. Conclusions

In this paper, the overall accuracy of the classified satellite image is *70.64075%*, which can be rised to be about *81.83279%* when regarding both Resident without vegetation and Resident with vegetation classes as same class. Where the used of quadtree serves the classification stage due to the block size was smaller time by time till reaching to spectrally homogenous region. And, the classification results of SVD method show that the variation of each class in both user's accuracy and producer accuracy, where the user's accuracy classes: water, resident With Vegetation, and Open Land class are greater than their producer accuracy, while the user's accuracy of Vegetation and Resident without vegetation are less than the producer accuracy of the standard classified image, which indicates the classes of water, Resident with vegetation and, Vegetation are more changed compared with the other classes.

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