

## Image Integration Based Ant Colony System for Multiband Satellite Image Classification

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### Abstract

The motivation we address in this paper is to find out a generic method used to classify conceptual satellite image taken in multiband imagery. Predefined training image with different imagery bands is considered to test the proposed classification method. The Korhunen-Loeve (KL) transform is first employed to create newly integrated image with dense information and best contrast due to the information of all used bands are concentrated in one integral image. Then, the integrated image is partitioned into variable sized blocks using hybrid horizontal-vertical (HHV) partitioning method. The size of blocks is determined automatically according to the spectral uniformity measurements. Later, ant colony optimization (ACO) is used to find out the optimal number of classes that may exist in the image, and then classify the image in terms of the discovered classes. It was found that the obtained classification results by ACO are in a good agreement with the actual training data, which ensure the success of the proposed method and the effective performance of the classification.

Keywords: Satellite image classification, Image integration, ACO.

### Introduction

Image classification is a fundamental problem in the image analysis discipline; it plays an important part in the image processing since it has been one of the most difficult tasks due to the complexity and diversity of such images. Classifying an image aims at dividing the image into homogeneous zones delimited by boundaries so as to separate the different entities visible in the image [1]. A great deal of classification methods has been proposed in the last thirty years. However, an important question to solve is how to benchmark these methods and evaluate their robustness with respect to a given real-life application.

Recently, many researchers have focused their attention on a new class of algorithms, called metaheuristic. A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems. In other words, a metaheuristic can be seen as a general-purpose heuristic method designed to guide an underlying problem specific heuristic toward promising regions of the search space containing high quality solutions. Therefore, a metaheuristic is a general algorithmic framework, which can be applied to different optimization problems with relatively few

modifications to make them, adapted to a specific problem [2]. The use of metaheuristics has significantly increased the ability of finding very high-quality solutions to hard, practically relevant combinatorial optimization problems in a reasonable time. This is particularly true for large and poorly understood problems. Several metaheuristics, such as Genetic Algorithms (GA) [3], Tabu Search and Simulated Annealing [4], have been proposed to deal with the computationally intractable problems. Ant colony optimization (ACO) is also new metaheuristic developed for composing approximate solutions [5]. The ant algorithm was first proposed by Colomi et al., and has been receiving extensive attention due to its successful applications to many combinatorial optimization problems [6]. Like genetic algorithm and simulated annealing approaches, the ant algorithms also foster its solution strategy through use of nature metaphors. The ACO is based upon the behaviors of ants that they exhibit when looking for a path to the advantage of their colony. Unlike simulated annealing or Tabu search, in which a single agent is deployed for a single beam session, ACO and GA use multiple agents, each of which has its individual decision made based upon collective memory or knowledge.

Recently, the ACO metaheuristic has been proposed to provide a unifying framework for most applications of ant algorithms to combinatorial optimization problems [7]. Algorithms that actually are instantiations of the ACO metaheuristic will be called ACO algorithms. This paper aims to investigate the ability of the Ant Colony Optimization (ACO) hybrid with an image integration method to solve the problem of classifying various areas of satellite images in terms of its semantic concepts.

### **Problem Statement**

The main behavior of many satellite image partitioning methods does not observe the fine details or boundaries of each part; they look at the generic attributes that dominate the fine details that may be found in each part. Almost, this approximation is set with some predefined restrictions (such as threshold) help to guide the partitioning process. The proper value of these restrictions leads to acceptable results. The motivation we address in this paper is to overcome such a problem using an image integration technique. Image integration makes the fine details to be shown clearly, such that good partitioning can be achieved. Moreover, to credit efficient partitioning, a hybrid partitioning method is employed. Hybrid method uses the quadtree within the horizontal-vertical method to credit best partitioning that results in spectrally homogeneous blocks. As a result, good partitioning makes the classification by ACO to be optimized well. The optimization yields the actual number of classes that may be found in the image, and shows the classified image in terms of the resulting classes.

### **Related Works and Contribution**

The problem of image segmentation and classification has attracted a lot of research. The search frequently was about accurate methods that are needed to improve the field of application. The most interesting studies besides our contribution are briefly mentioned in the following subsections:

#### **Related Works**

There are many papers devoted to satellite image classification. They differ in many aspects such as; material images, used approach, or even the application limitations.

Below we shall focus on some researches that deal with the problem of accounting for the most of image details through the classification process in different fields of applications:

The feasibility of using genetic algorithms to segment colored images is investigated in [8], a detailed discussion for issues involved in designing such algorithms are presented. This prepares to find out a hybrid genetic supervised classification technique to evolve automatic feature extraction algorithms that are proposed in [9] using multispectral imagery technique, which showed an acceptable result achieved by GA. Also, an automatic construction of image classification based on genetic image network for image classification (GIN-IC) was proposed in [10]. This technique transformed original images to easier-to-classify images using image transformation nodes, and selects adequate image features using feature extraction nodes. It's proved that the use of image transformation nodes is effective for image classification problems. Recently, an evolutionary computing to fractal image compression was introduced in [11]. The use of evolutionary computing was motivated to find good partitioning. This showed that a far better rate distortion curve can be obtained with this approach as compared to traditional quadtree partitioning.

Evolutionary based researches include also the satellite and land cover imaging, the literature in [12] suggests designing a suitable image processing procedure as a prerequisite for a successful classification of remotely sensed data into a thematic map. Effective use of multiple features of remotely sensed data and the selection of a suitable classification method are especially significant for improving classification accuracy. The probability densities associated with the image pixel intensities within each region are assumed in [13] to be completely unknown a priori. The information-theoretic optimization problem was solved by deriving the associated gradient flows and applying curve evolution techniques. The experimental results based on both synthetic and real images demonstrate that the proposed technique can solve a variety of challenging image classification problems.

In the field of object segmentation and recognition, many studies based on

evolutionary algorithms were considered. In [14] a segmentation method was proposed using a classification subsystem as an integral part of the segmentation, which provided contextual information regarding the objects to be segmented. The motivation was segmentation and classification follows the wrapper methods of feature selection. It was shown that the performance of wrapper-segmentation based on real-world and complex images of automotive vehicle occupants. Whereas the experiment in [15] proves that the particle swarm optimization (PSO) is suitable for selecting good individual features and evolving associated weak classifiers is more effective than for selecting features. Also it showed that PSO can evolve and select meaningful features in the face detection task.

The field of computer aided diagnosis is also employed the evolutionary methods, some achievements were obtained depending on some tests that ensure the ability of the evolutionary algorithms to give high efficient classification. In [16] a swarming-agent based intelligence algorithm was proposed using a hybrid ACO and PSO algorithms to identify the diagnostic proteomic patterns of biomarkers for early detection of ovarian cancer. The proposed system also gives the second opinion for the pathologist regarding the condition of the ovary. The robustness of such method comes from the narrow band of image viewing. The automated diagnosis research was handled in [17] by building a software system that provides expert diagnosis of breast cancer based on three step of cytological image analysis. The first step is based on segmentation using an active contour for cell tracking and isolating of the nucleus in the studied image. Then from this nucleus, some textural features have been extracted using the wavelet transforms to characterize the image using its texture, so that malign texture can be differentiated from benign on the assumption that tumoral texture is different from the texture of other kinds of tissues. Finally, the obtained features will be introduced as the input vector of a Multi-Layer Perceptron (MLP), to classify the images into malign and benign ones. Later, an unsupervised image classification using a

Kohonen self-organizing map neural network was discussed. Two-dimensional discrete wavelet transforms decompose magnetic resonance images (MRI) into the small size and de-noise the approximation images [18]. Kohonen self-organizing map neural network is trained with approximation image, then trained neural network classify pixels of original image. This technique showed very encouraging level of performance for the problem of classification in MRI image of the human head.

### **Our Contribution**

Previous studies point out the ability of evolutionary algorithms to achieve a desired solution with high precision. The ant colony optimization (ACO) is handled to establish an accurate method for image classification to be applied on multi bands satellite images of expanded diversity range of concepts. The interesting contribution in this work is employing KL transform to integrate the image cues before the image partitioning. The integrated image pass through hybrid HV (HHV) based partitioning. The proposed HHV method is inspired from the HV partitioning method, the adaptation of HHV summarized by including the well-known quadtree method within. HHV method goes to partition the target image into variable size parts. Such method possesses some benefits over the HV or quadtree, which is the high accuracy of the partitioning; this guarantees the acceptable homogeneity for image parts. Such partitioning paved the way for the ant colony system to classify the satellite image properly. Later, Ant Colony Optimization (ACO) is used to estimate the number of classes that may be found in the image, and then classify the image according to the determined classes.

### **Ant Colony System**

Ant colony system (ACS) was adopted to find the optimal solutions for many applications. Ant colony optimization (ACO) was inspired from the real ant's behavior, where a very interesting aspect for the behavior of several ants is their ability to find shortest paths between the ants nest and the food source [19], this is done with help of depositing some ants to a chemical material called pheromone, so if there is no pheromone

trails ant move essentially at random, but in the presence of pheromone they have a tendency to follow the trails. Experiments show that ants prefer paths that are marked by high pheromone concentration, the stronger pheromone trail in a path, then this path will have higher desirability and because ants follow that path they will intern deposited more pheromone on the path and they will reinforce the paths, this mechanism allows the ants to discover the shortest path, this shortest path get another enforcement by noting that the pheromone evaporates after some time, in this way the less promising paths progressively loss pheromone because less and less ants will use these paths [20]. This behavioral phenomenon of ants is employed to be adapted as an optimization method. The ACS achievements and the mathematical basis of its use for optimization are explained in the following:

### ACS Achievements

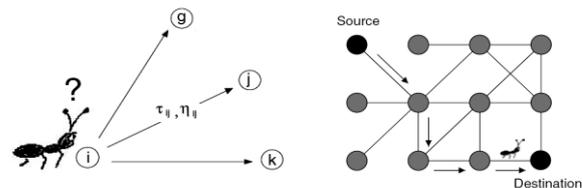
Ant algorithm was first proposed by Dorigo and Colleagues as a multi-agent approach to difficult combinatorial optimization problems like the traveling sales man problem (TSP), quadratic assignment problem (QAP), and later introduce the ant colony optimization (ACO) metaheuristic [21]. There is currently a lot of on going activity in the scientific community to apply ant based algorithms to many different discrete optimization problems. Recent applications cover problems like vehicle routing problem (VRP) [22], graph coloring [23], and routing in communication network [24].

### ACS for Optimization

Ant colony optimization algorithms represent special solution approaches for combinatorial problems derived from the field of swarm intelligence. The solution approach consists of  $n$  cycles in each cycle first each of the  $m$  ants constructs a feasible solution. In ACS each ant built a complete tour that visits all nodes. Obviously, this solution neither has to be optimal nor must it be even close to the (unknown) optimal value. Improved solutions can be obtained if the knowledge gathered by other ants in the past on how good solutions can be obtained is incorporated into the ant's decisions. To show that, assume that an ant is

located in node  $i$ . To choose the next node  $j$  that has not yet been visited by that ant, see Fig. (1), one may apply one of the following two randomized strategies [25]:

1. *Constrictive heuristic*; apply one priority role like randomized nearest neighbor. Decision values for all nodes  $j$  are determined by the inverse of the distance from the node  $i$  to that  $j$ . The next node the ant moves to is then randomly chosen according to the probabilities determined by those decision values. Consequently, if node  $j$  is closer to  $i$  than node  $g$  or  $k$ , it is more likely to choose node  $j$ . The decision values of the constructive heuristic will be later referred to as  $\eta_{ij}$ .



**Fig. (1) The possible paths may chosen by the ant.**

2. *Pheromone trails*; this strategy is mainly inspired by the way real ants find shortest paths, while commuting between two places on different possible paths ants deposited the chemical substance pheromone. The shorter the path is the more often the ant will use this path within a limited period of time and, consequently, the larger the amount of pheromone will be on that path. Thus, whenever an ant has two choices between different available paths it will prefer the one with higher amount of pheromone. The amount of the pheromone is initialized with 0 for all paths  $(i,j)$ . After an ant has completed a tour, the values of the cells that belong to the paths the ant has chosen are updated by the inverse of the obtained objective function value, i.e. the length of the tour. The amount of the pheromone trail  $\tau_{ij}$  associated to path  $(i,j)$  is intended to represent the learned desirability of choosing node  $j$  when in node  $i$ . consequently, paths belonging to good solutions receive a high amount of pheromone.

ACS algorithms combine these two strategies. The probability that ant  $v$  located in

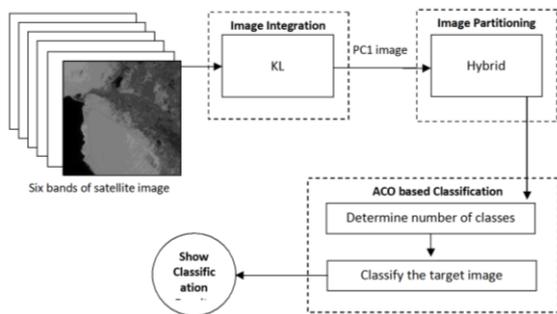
node  $i$  choose the next node  $j$  is determined by the following formula [25]:

$$P_{ij}^v = \begin{cases} \frac{(\tau_{ij})^\alpha (\eta_{ij})^\beta}{\sum_{k=1}^{N_i^v} (\tau_{ik})^\alpha (\eta_{ik})^\beta} & \text{if } j \in N_i^v \\ 0 & \text{otherwise} \end{cases} \dots\dots\dots(1)$$

Where,  $\alpha$  and  $\beta$  are given weighting factors and  $N_i^v$  is the set of nodes that have not yet been visited by ant currently located in node  $i$ .

**Proposed Classification Method**

The proposed metaheuristic classification method includes three main stages: the first stage aims at integrating the spectral contents found in the test bands into a concentrated one integral image. The second stage is hybrid HV based partitioning (HHV), which is used to partition the target image into sub regions. The robustness of such method is due to its ability to effectively partitioning diversity regions in the satellite image. Later stage, the ACO is adopted to perform the unsupervised classification that classifies the target image and obtains the members of each class. Fig. (2) shows the three stages of the proposed classification system, each one is explained with details in the following subsections:



**Fig. (2) The proposed classification system.**

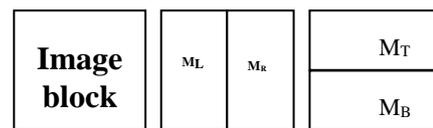
**5.1 Image Integration**

The use of different imagery bands lead to get different details in the area under test; this enabled us to collect greater details to be represented in one image using Korhunen-Loeve (KL) transforms [26]. KL transform uses the input image bands to create new other principles components (PCs) bands. The newly created image will have characteristics of dense information and best contrast. Many

literatures mentioned that the first PC image contains about 75% of the information carried by the input images [26], this makes the first PC is suitable for the purpose of classifying the multiband satellite image, whereas the other remaining PCs are ignored. The chosen PC image is the most descriptive and ready to apply the partitioning stage on it.

**Hybrid Horizontal-Vertical Partitioning**

The hybrid HV (HHV) partitioning method is based on computing the direction difference between the mean of gray levels of the top-bottom and left-right halves of image blocks as shown in Fig. (3).



**Fig. (3) The implementation method to compute the means left, right, top, and bottom halves for the HV partitioning.**

These differences are computed using the following formulas:

$$D_H = \left| \sum_{i=0}^{H-1} \left\{ \sum_{j=0}^{\frac{w}{2}-1} g(i, j) - \sum_{j=\frac{w}{2}}^{w-1} g(i, j) \right\} \right| \dots\dots\dots(2)$$

$$D_V = \left| \sum_{i=0}^{w-1} \left\{ \sum_{j=0}^{\frac{H}{2}-1} g(i, j) - \sum_{j=\frac{H}{2}}^{H-1} g(i, j) \right\} \right| \dots\dots\dots(3)$$

where,  $g(i,j)$  is the pixel value at a position  $(i,j)$ .  $w$  is the block width,  $H$  is the block height,  $D_H$  is the horizontal difference, and  $D_V$  is the vertical deference.

The adaptation used to improve the mechanism of HV partitioning is the implementation of quadtree partitioning on each block that does not satisfy the uniformity criterion of HV partitioning. This adaptation will be referred to as hybrid HV partitioning. The tests showed improved efficiency of HHV in comparison with HV or quadtree. The implementation of the hybrid method can be demonstrated as follows [27];

- i. Compute the global mean ( $M$ ) and standard deviation of the input image, then the extended standard deviation, this value is adopted as a difference tolerance criterion (i.e. threshold).

- ii. Set the values of some partitioning control parameters which attributes to the segmentation process, these parameters are:
  - a. Maximum block size, it represents the maximum size of the block and it corresponds to the minimum depth of the three partitioning.
  - b. Minimum block size, it represents the minimum size of the block and it corresponds to the maximum depth of the three partitioning.
  - c. Acceptance ratio, it represents the ratio of the number of pixels whose values differ from the block mean by more than the expected extended standard deviation.
  - d. Inclusion factor, it represents the multiple factor that defines the value of the extended standard deviation when multiplied by the global standard deviation.
  - e. Mean factor, it represents the multiplication factor that define the value of the extended mean ( $M_e$ ) when multiplied by the global mean.

- iii. The HV segmentation information is stored by utilizing the HV Link List, which consists of the following fields:
  - a. *Position*: represents  $X$  and  $Y$  coordinates of the top-left corner of the image block.
  - b. *X-size and Y-size*: represent the width and height of the image block respectively.
  - c. *Next*: represents a pointer to the next block.

The segmentation process starts with subdividing the whole image into sub-blocks whose size is equal to the maximum block size.

- iv. For each sub block, check the directional uniformity criterion that is used as a measure to decide whether the sub-block will be partitioned into halves or not. The directional uniformity criterion was implemented by applying the following steps;
  - a. Sub divided each sub-block into four quarters and determines the mean values for each quarter ( $M_{LT}$ ,  $M_{RT}$ ,  $M_{LB}$ , and  $M_{RB}$ ), the subscript labels  $LT$ ,  $RT$ ,  $LB$ , and  $RB$  represent the left-top, right-top, left-

bottom, and right-bottom quarters respectively.

- b. Calculate the mean values of the left half ( $M_L$ ), and right half ( $M_R$ ), top half ( $M_T$ ), and bottom half ( $M_B$ ) as follows:

$$\begin{aligned}
 M_L &= (M_{TL} + M_{BL}) / 2 \\
 M_T &= (M_{TL} + M_{TR}) / 2 \dots\dots\dots (4) \\
 M_R &= (M_{RT} + M_{RB}) / 2 \\
 M_B &= (M_{BL} + M_{BR}) / 2
 \end{aligned}$$

Then, determine the horizontal and vertical differences as follows:

$$\begin{aligned}
 D_H &= |M_L - M_R| \\
 D_V &= |M_T - M_B| \dots\dots\dots (5)
 \end{aligned}$$

- c. If  $D_H > D_V$ ,  $D_H < M_e$ , and  $X\text{-size} > \text{Minimum block size}$ , then a horizontal partitioning decision was taken. If  $D_V > D_H$ ,  $D_V > M_e$ , and  $Y\text{-size} > \text{minimum block size}$  then a vertical partitioning decision was taken. Otherwise quadtree partitioning decision was taken when the block satisfies the uniformity condition of quadtree partitioning.

- d. After completing the partitioning, the latest update occurred in the link list is stored in a kernels map to show the neighbors of each part.

**ACO for Classification**

This stage begins with computing the gray median ( $M_i$ ) and gray variance ( $V_i$ ) for each image part, where the subscript  $i$  is pointer refers to the current part of the image. The total variance  $V_T$  is the average variance of  $V_i$  is computed to determine the rate of deviating each class from others. Each image part is a kernel specified by one feature;  $M_i$ , which is stored in a solution matrix. There are two goals for this stage: (1) to estimate the optimal number of classes may found in the image, and (2) to find out the optimal label (class) for each kernel in the image. Initially assign the values of number of iteration ( $n$ ), number of ants ( $m$ ), and initial pheromone value ( $\tau_o$ ). For each kernel, the initial amount of pheromone is  $\tau_o$ , and there are  $m$  of ants begin to move from. Using the kernel map, each ant should select a kernel for the next movement that is not selected previously. To find out if a kernel is being selected or not, a flag value is assigned for each kernel. The flag values are set to be 0 at each time when new ant gets down; once the

kernel is selected the flag is changed to 1. The first ant remains moving until there is no choices are found, another ant will be get down in the same kernel, and so on until the last ant. This procedure is followed for all the kernels. Each time when the ant randomly selects the  $k^{th}$  kernel, the median  $M_k$  is stored in the solution matrix, and the pheromone updated using the following equation.

$$\tau_{new} = (1 - \rho)\tau_{old} + \rho\tau_o \dots\dots\dots(6)$$

Where,  $\tau_{new}$  and  $\tau_{old}$  are the new and old pheromone values of the current kernel, and  $\rho$  is rate of pheromone evaporation parameter ( $0 < \rho < 1$ ). When the ant completes its tour, calculate the average of the medians ( $Am$ ) of the selected kernels by each ant using the solution matrix. The  $Am$  is the average of the kernels median that individual ant chooses them in one tour. If the label of  $Am$  is originally found in the solution matrix even at amount of deviation  $V_T$  (i.e.  $Am \pm V_T$ ) then leave it, otherwise assign new label to  $Am$  and store it in the solution matrix. After completing all kernels, the process of ants getting down is repeated  $n$  times. The number of labels in the solution matrix is the number of classes ( $N_c$ ) in the image. The image is then classified by minimizing the distance between its kernel medians ( $M_i$ ) and the label values ( $Am$ ) found in the solution matrix with acceptable deviation  $V_T$ . The following steps summarize the algorithm of ACO for image classification.

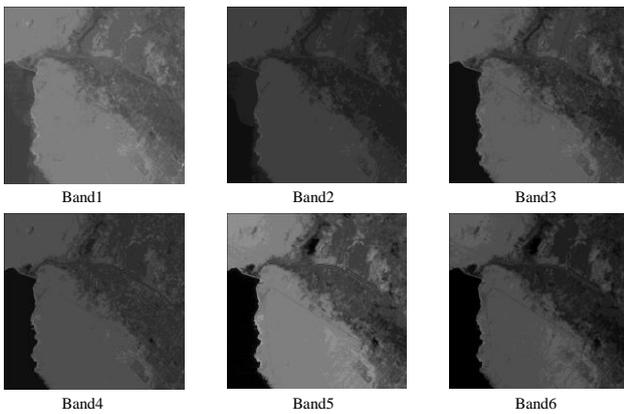
1. For each kernel ( $i^{th}$ ) in the image, calculate the median  $M_i$  and variance  $V_i$  values.
2. Initialize the values of number of iterations ( $n$ ), number of ants ( $m$ ), initial pheromone value ( $\tau_o$ ), and a constant value for pheromone update ( $\rho$ ).
3. Create a solution matrix ( $S$ ) to store the labels,  $M_i$ , flag, pheromone for each kernel.
4. Get new  $i^{th}$  kernel in the image
5. Let new ant get down to the  $i^{th}$  kernel, make the flag to be zeros.
6. Select a random kernel, which is not selected previously, according to the probabilistic choice in equation (1); at which

$$\eta_{ij} = \frac{1}{d_{ij}}, \text{ and } d_{ij} = M_i - M_j.$$

7. Update the pheromone values for the selected kernels by the current ant.
8. Perform steps 6-7 until no possible choices for the current ant.
9. Assign unique label for the kernels visited by the current ant, store them in  $S$ .
10. Perform steps 5-9 for  $m$  ants.
11. Do steps 4-10 until last kernel found in the image.
12. Back to step 5 for  $n$  times.
13. Compute the number of labels (classes)  $N_c$ .
14. Kernels with same  $Am$  have same labels.
15. Assign a specific color for each label in the solution matrix, and draw the image with the new coloring, that is the classified image.

### Test Images

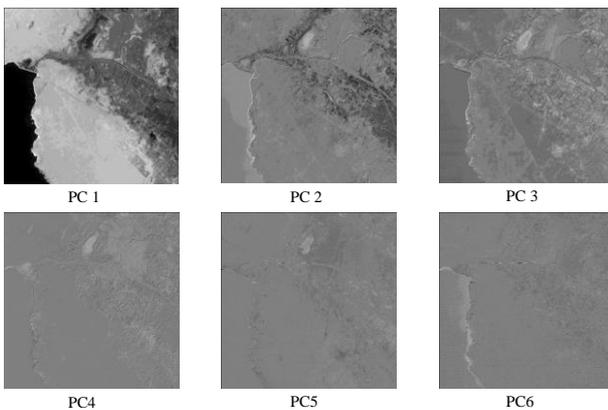
The satellite images used in the test of this research is Thematic Mapper (TM) image bands provided by the Space Research Center of Iraq. Thematic mapper images are usually found in different six multi-spectral bands. Fig.(4) presents TM image collection of the studied area in the west of Iraq (flight path 169 and row 37). The collection contains 6 images; each appears different fine details related to spectral imaging range. These images collection was taken to a wide conceptual range of contents in the land with acceptable spatial resolution  $512 \times 512$  pixels. Different concepts in this image such as (water, urban, bare, and vegetation) gained its importance in the field of satellite image classification. Many studies were made on these bands for the purpose of classification; the investigation refers to finding 7 training classes [26]. This result enables to test the performance of the proposed HHV and ACO method for the purpose of satellite image classification.



**Fig. (4) The material images used in the present work.**

**Results**

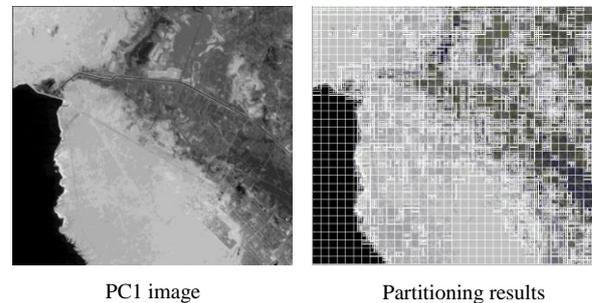
In the following, the results of each stage is presented and discussed separately: Fig.(5) displays the six PC images resulted from the KL transform. It is shown that just the first PC image is integrated well since it shows the fine details clearly in comparison with the input ones presented in Fig.(4) or the other PC images.



**Fig (5): The resulted PC images by means KL transform.**

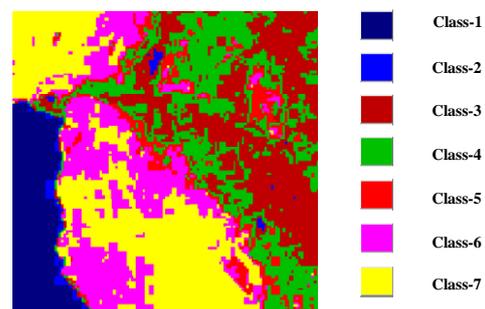
Fig.(6) shows the partitioning results using hybrid HV applied on the PC1 image. It is observed that the shape and size of the image parts are variable. Some parts are horizontal or vertical rectangle due to the use of HV partitioning, whereas other parts are squared due to the use quadtree partitioning. The image region of fine details is shown partitioned with quadtree, while the expanded smoothed region is partitioned by the HV. In all parts, the block size was automatically determined according to the details variety. Almost, the block takes a small size at the region of more details,

whereas it is becomes relatively larger at few detailed region. The true partitioning makes the application of ACO to be more confident. The ACO for classification was applied with the following setting;  $n=100$ ,  $m=50$ ,  $\rho=0.1$ ,  $\tau_o=1$ ,  $\alpha=1$  and  $\beta=1$ . Therefore, the optimal number of classes determined by ACO was seven ( $N_c=7$ ).

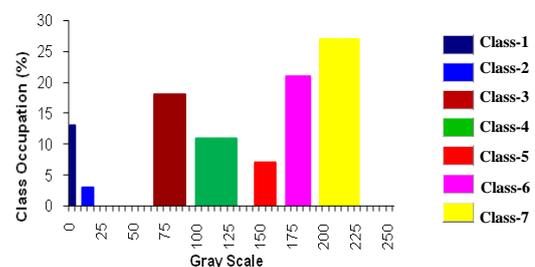


**Fig. (6) The PC1 image and its partitioning results using HHV.**

Fig. (7) shows the classified image and Fig. (8) shows the distribution of the seven classes extended along the gray scale, the bar height is the percent of each class occupation in the image while bar width refers to the extension of each class in the image. It was observed that true partitioning greatly help the ACO to determine the optimal number of classes, which absolutely leads to optimal classification.



**Fig. (7) The classification results using ACO.**



**Fig. (8) The distribution of classes along the gray scale.**

### Analytical Observation

It is observed that the proposed method was able to find effectively the optimal solution for the problem of multiband satellite image classification. The classification results showed that the choice of variable block size improves the classification results, because the block size was assumed to be dynamic, and it was determined only whenever the most of block contents become spectrally homogenous. The use of image integration shows higher chromaticity and details in the PC image, which leads almost to greater description than the original image bands. Also, it is noticeable that ACO for image classification was successful in finding the proper number of classes in the target image. It was seen that the gray images are classified according to the spectral variation appeared in the image. Since the image contained expanded regions of different concepts, each class was fitted to include a specific region. One can note the number of classes was a measure for the amount of the details appeared in the image. Indeed, the chromaticity do not greatly serves the classification of satellite images, so the classification found occurred just depending on the spectral variety. In spite of the block shape was rectangle or square, which expect to covers different concepts within especially at the edges, there was no confusion occurred due to the use of median gray instead of the mean to define each block in the ACO. Such that, the ACO was found classify the blocks in terms of the dominant concept in each block. This ensures the ability of the image integration based ACO to make accurate classification since it is related to the image decomposition in terms of spectral details and intensity distribution. In general, the ACO method for classification purposes was successfully proved good results (which is agree to the results obtained in reference 26) to classify multiband satellite images, which ensure the efficiency of the employed method and the good performance of the classification.

### Conclusions and Further Work

Some conclusions can be driven from the analyses of the ACO behavior for image classification. The primary stage of partitioning was accurately partitioned the image depending on the spectral uniformity,

such that the founded block size differs from region to another in the image depending on the details found in that region. The use of ACO was successfully determining the number of classes in the image and showed good classification results, which ensure the robustness of the ACO to optimize the image classification. For further work, we suggest using a clustering step after the ACO for determining the optimal number of classes. Also, one can use GA hybrid with ACO frequently to guide the classification into more accurate results.

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#### الخلاصة

هدف هذا البحث هو ايجاد طريقة عامة لتصنيف صور الاقمار الصناعية مصورة بحزم متعددة ذات مفاهيم تعبيرية مختلفة. ولذلك تم استخدام صورة اقمار صناعية مأخوذة بحزم مختلفة ذات مناطق تجريبية معرّفة لأختبار طريقة التصنيف المقترحة. استُخدم تحويل KL أولاً لصناعة صورة جديدة متكاملة بمعلومات كثيفة وتباين افضل وذلك بتجميع معلومات كل الحزم في الصورة المتكاملة . تم تجزئة الصورة المتكاملة الى اجزاء متغيرة الحجم باستخدام طريقة التجزئة الافقية-العمودية الهجينة (HHV). ان حجم جزء الصورة يحدد ذاتياً طبقاً الى مقاييس الانتظامية الطيفية. بعد ذلك أُستخدمت خوارزمية مستعمرة النمل (ACO) لايجاد عدد الاصناف الامثل في الصورة. ومن ثم صُنفت الصورة بدلالة الاصناف المكتشفة. ان نتائج التصنيف المستحصلة بواسطة خوارزمية مستعمرة النمل كانت تطابق البيانات التجريبية، وهذا يؤكد نجاح الطريقة المعتمدة وكفاءة اداء عملية التصنيف.