



ANT COLONY SYSTEM WITH MEDIAN BASED PARTITIONING FOR IMAGE SEGMENTATION AND CLASSIFICATION

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Abstract

The motivation we address in this paper is to find out a generic method used to segment and classify different types of conceptual images. A novel median based method was proposed as primary stage for image segmentation, in which the image is partitioned into fixed sized quadrants called kernels. The size of kernels in a specific image is determined according to the spectral uniformity measurements. Later, Ant Colony Optimization (ACO) is used to find out the optimal number of classes may exist in the image, and then classify the image in terms of the determined classes. Different types of images with different semantic concepts were used to test the proposed classification method. The results obtained by ACP ensure the success of the proposed method and the effective performance of classification.

نظام مستعمرة النمل مع التجزئة الوسيطة لتقطيع الصور وتصنيفها

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الخلاصة

ان الهدف من هذا البحث هو ايجاد طريقة لتجزئة وتصنيف الصور بحيث تكون شاملة لجميع انواع الصور بمختلف مفاهيمها التعبيرية. ولذلك تم اقتراح طريقة جديدة مبنية على حسابات الوسيط كمرحلة اولية لتصنيف الصور، وفيها تجزأ الصورة الى بلوكات منتظمة الحجم. ان حجم البلوكات في صورة معينة يُحدد طبقاً الى مقاييس الانتظامية الطيفية. بعد ذلك أُستخدمت خوارزمية مستعمرة النمل (ACO) لاجاد عدد الاصناف الامثل للصورة. ومن ثم صنفت الصورة بدلالة الاصناف المُحددة. ولأجل اختيار طريقة التصنيف المقترحة، أُستخدمت صور ذات مفاهيم وصفية مختلفة. كانت نتائج التصنيف المستحصلة بواسطة طريقة مستعمرة النمل (ACO) واقعية وهي تؤكد نجاح الطريقة المعتمدة وكفاءة اداء عملية التصنيف.

1. Introduction

Image segmentation and classification are two fundamental problems in image analysis. Both play an important part in image processing; each has been one of the most difficult tasks due to the complexity and diversity of images. Segmenting an image aims at dividing the image into homogeneous zones delimited by boundaries so as

to separate the different entities visible in the image. Classification consists in labeling the various components visible in an (image 1). A great deal of segmentation and 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 Colormi 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 [7]. to combinatorial optimization problems. 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 a novel partitioning method to solve the problem of

classifying a varsity range of images in terms of its types and semantic concepts.

2. Problem Statement

The main behavior of many images segmentation methods does not observing the fine details or boundaries of each segment; they look at the generic attributes that dominant fine details that may found in each segment. Almost, this approximation is set with some predefined restrictions (such as threshold) help to guide the segmentation process. The proper value of these restrictions leads to acceptable results. The motivation we address in this paper is to overcome the problem of finding the restrictions, this is carried out by proposing a heuristic partitioning method hybrid with ACO used to efficiently segment the images whatever their type or concept.

3. Related Work

There are many papers devoted to image segmentation and classification. They differ in many aspects such as; material images, used approach, or even the application limitations. The feasibility of using genetic algorithms to segment general color 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 as proposed in [9]. using multispectral imagery, which showed an acceptable results 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 proved the use of image transformation nodes is effective for image classification problems. Recently, an evolutionary computing to fractal image compression was introduces 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 includes also the satellite and land cover imaging, the literature in

[12]. suggests designing a suitable image processing procedure is 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. 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. Whereas the experiment in [15]. prove the particle swarm optimization (PSO) is suitable for selecting good individual features and evolving associated weak classifiers is more effective than for selecting features.

The field of computer aided diagnosis is also employed the evolutionary methods. 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. Also, an 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 method is based on segmenting the image using an active contour for cell tracking and isolating of the nucleus in the studied image. Then extracting some textural features using the wavelet transforms to characterize the test image, 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. Two-dimensional discrete wavelet transforms decompose magnetic resonance images (MRI) into the small size and denoise approximation images in [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 segmentation in MRI image of the human head.

4. Our Contribution

Previous studies point out to the ability of evolutionary algorithms to achieve a desired solution with high precision, such that ant colony optimization (ACO) is employed to establish a generic method for image classification that enable to classify an expanded diversity range of conceptual images. Therefore, ant colony optimization based approach is handled to be applied on different natural and man-made images that pass through a newly proposed median based partitioning at before stage. The proposed median based partitioning (MBP) method is inspired from the well-known quadtree method. MBP method goes to partition the target image into fixed size and uniform segments. Such method possesses some benefits over quadtree, which is high precision beside to the fastness and simplicity. Overall, such partitioning guarantees the acceptable homogeneity for image segments; that means it paved the way for the ant colony system to classify the image properly. In addition, the interested point in this work is employing the ACO to estimate the number of classes may found in each image, which is, off course, varying from image to another, this is the reason of using different types and different semantic concepts of images.

5. 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.

A lot of achievements of such optimization obtained using ACO. 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].

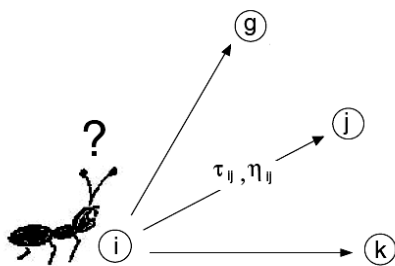


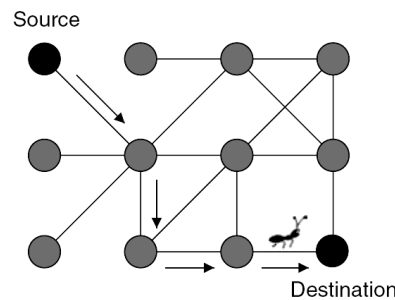
Figure 1: The possible paths may chosen by ants [25].

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 η_{ij} [25].

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

6. 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 Figure 1), one may apply one of the following two randomized strategies [25]:



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 ants 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 τ_{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]:

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

Where, α and β 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 .

used to partition the target image into sub regions. The robustness of such method is due to its ability to effectively partitioning diversity conceptual images. Latter stage is the use of ACO to unsupervised classifies the target image and obtains the members of each class. (Figure 2) shows the overall proposed system, each one is explained with details in the following subsections.

7. Overall Approach

The overall metaheuristic classification approach includes two main stages within: first, the median based partitioning (MBP), which is

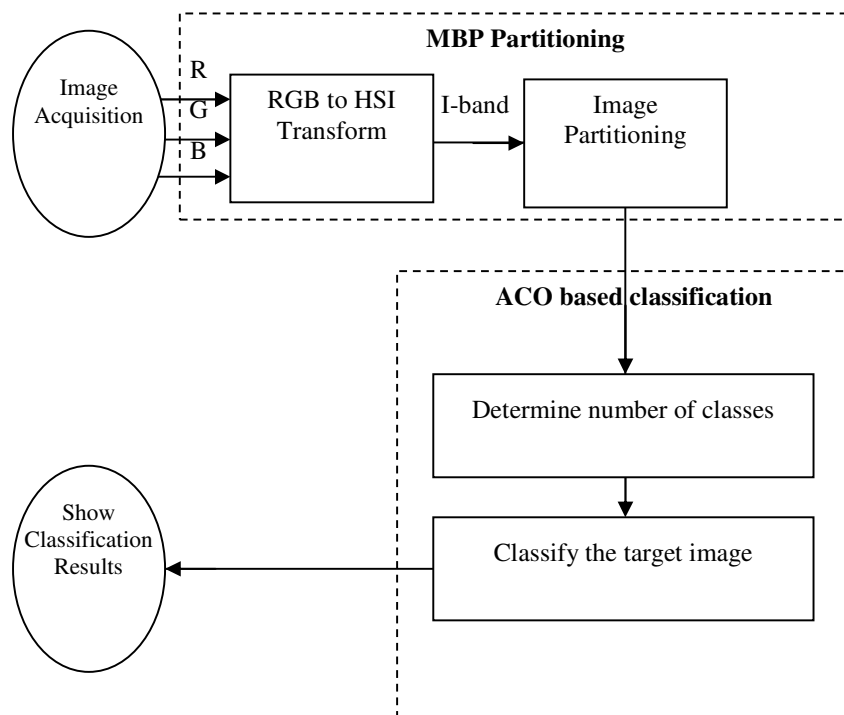


Figure 2: Diagram of the overall classification system.

7.1 Median Based Partitioning (MBP)

The MBP is a novel method proposed for the purpose of present stage. The generic idea of such method is inspired from the well-known quadtree method. It depends on the amount of spectral variation for the image regions. To ensure the correct estimation for the spectral variation, the colored image should be transformed from the RGB into HIS representation by using the following equations [12]:

$$\begin{aligned}
 H &= -44R - 87G + 131B \\
 S &= 131R - 110G - 21B \dots\dots\dots (2) \\
 I &= 77R + 150G + 29B
 \end{aligned}$$

By this way, all the information distributed between the RGB bands of the image are collected in one concentrated band, which is the intensity band (I-band). For the purpose of classification, shades found in I-band will express the amount of chromaticity in the image. Next, whole the applied operations will fall in the domain of I-band, whereas the other two bands H and S are neglected since they just describe the chromatic distribution and do not carry any spectral information. The process of partitioning is begin first by partitioning the image (I-band) into four (i.e. $N_p=4$) equal quadrants (kernels), the median and variance are calculated for each kernel in the image as follows

$$V_k = \frac{1}{w_k \times h_k} \sum_{i=0}^{w_k-1} \sum_{j=0}^{h_k-1} |f_{ij} - M_k| \dots\dots\dots (3)$$

Where, M_k and V_k are the median and variance of the k^{th} kernel ($k=1,2,\dots N_p$) in the image, w_k and h_k are the width and height of the k^{th} kernel, f_{ij} is the pixel intensity value found in the location (i,j) , and N_p is the number of kernels found in the image. Each kernel in the image is now checked, if its variance (V_k) is greater than a threshold (T_1 ; is 1/5 the range of the image contrast, where the contrast is the total variance of the image) then a specific counter N (prepared for this purpose) will be increased by one. After all kernels are checked, the partitioning is doubled (i.e. each kernel is repartitioned to four others) when the counter N is greater than T_2 (T_2 is 2/3 the total number of kernels in the image). Otherwise, the partitioning is stopped. The process of repartitioning will be continued till the stop condition is terminated or achieving smallest allowed size of kernels (i.e. 4×4). The kernel size (B_s) is equal to the image size ($w \times h$)

divided by the number of kernels (N_p). As a result, we achieve spectral homogeneous kernels as image segments. Whole kernels have the same size, which is determined at the last partitioning cycle. The following subsequent algorithm describes how implement the proposed method to segment the material image into spectrally uniform regions.

1. Let N_p is the number of kernels in the image, initially $N_p=1$.
2. Compute the total variance of the image (V_T)
3. Compute $T_1=V_T/3$.
4. Make $N_p=4 \times N_p$, Partitioning the image into N_p quadrants
5. Compute $T_2=2 \times N_p/5$, $B_s=w \times h/N_p$
6. For the k^{th} kernel, find the median M_k and variance V_k .
7. If $V_k > T_1$ then $N=N+1$.
8. Get new k^{th} kernel, and back to step 5
9. If $(N < T_2)$ or $(B_s > 4)$ then back to step 4.
10. Else: stop the partitioning process.

7.2 ACO for Classification

In this stage, the results of the partitioning stage; M_i , and V_i for each kernel are 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 for each kernel in the image. Initially assign the values of number of iteration (n), number of ants (m), and initial pheromone value (τ_o). For each kernel, the initial amount of pheromone is τ_o , and there are m of ants begin to move from. Each ant should select a kernel for the next movement that is not selected previously. To find out the kernels is been 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 and variance V_k are stored in the solution matrix, and the pheromone updated using the following equation [8].

$$\tau_{new} = (1 - \rho)\tau_{old} + \rho\tau_o \dots\dots\dots (4)$$

Where, τ_{new} and τ_{old} are the new and old pheromone values of the current kernel, and ρ

is rate of pheromone evaporation parameter ($0 < \rho < 1$). When the ant completes its tour, calculate the average of the medians (Am) and the average of variances (Vm) 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. After completing all kernels, the number of classes (N_c) can be determined to be equal the half average of Am for all the ant's tours. The reason behind that is because the human eye can distinguish the differences between at least four gray levels; so that the number of classes is assumed to be equal double the average of Vm (on both sides between the median) divided by four, i.e.

$$N_c = \frac{2 \times \frac{1}{B_s} \sum_{i=1}^{B_s} Vm_i}{4} = \frac{1}{2} \times \frac{1}{B_s} \sum_{i=1}^{B_s} Vm_i \dots (5)$$

Then the image is now unsupervised classified by minimizing the distance between its average medians (Am) and the class that belong to. The following steps summarize the algorithm of ACS for image classification.

1. For each kernel (k^{th}) in the image, calculate the median M_k and variance V_k values.
2. Initialize the values of number of iterations (n), number of ants (m), initial pheromone value (τ_0), a constant value for pheromone update (ρ).
3. Create a solution matrix (S) to store the labels, M_k , V_k , flag, pheromone for each kernel.
4. Get new k^{th} kernel in the image
5. Let new ant get down to the k^{th} kernel, make the flag to be zeros.
6. Select a random kernel, which is not selected previously, according to a probabilistic choice.
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 labeling (classes) using eq.(5).
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.

8. Test Images

The material images collection that used in this research was taken from a wide conceptual range of imaging techniques. Beside to the satellite image, natural and man-made images of high resolution (i.e. 800×800) were included. The collection contains 12 images of different fine details related to spectral and coloring distributions.

The purpose of using different semantic concept images is to examine the performance of proposed MBP and ACO for classification purpose.

Such that, the considered images include all the types may be found in the field of digital image processing, these types are; [1] Bi-level (mono chromatic) images, where the pixels can have one of two values, normally referred to as black and white as shown in Figure (3-a and b). Such images are useful to evaluate the segmentation results across boundaries. [2] Grayscale images, a pixel in such images can have one of the 2^n -values, indicating one of 2^n shades of gray. Thus, a gray scale image has n bitplanes. The images of the natural scene shown in Figure (3-c and d) are such example, which useful to test the optimal number of classes found in the image. [3] Satellite images that characterized by its fine details. These images may be found in one band or multi-bands. The images presents in Figure (3-e and f) are satellite images considered to check the classification sensitivity to labeling the fine details. [4] Discrete tone image, which is normally an artificial image. It may have few colors or many colors, but it does not have the noise and blurring of a natural image such as a personal images or TV images that shown in Figure (3-g and h). [5] Continuous tone images; this type of images can have many similar colors. The adjacent pixels in such images may differ by just 1 *unit*, it is hard or even impossible for the eye to distinguish their colors. A pixel in such an image is represented by either a single large number or by three components. A continuous tone image is normally a natural image such as the pictures shown in Figure (3-i and j). This type of images can indicate the classification behavior of the proposed technique. And finally, [6]

Cartoon like image, this is a color image that consists of uniform areas. Each area has a uniform color, but adjacent area may have very

different colors as shown in Figure (3-k and m). These images are useful to estimates the segmentation performance.

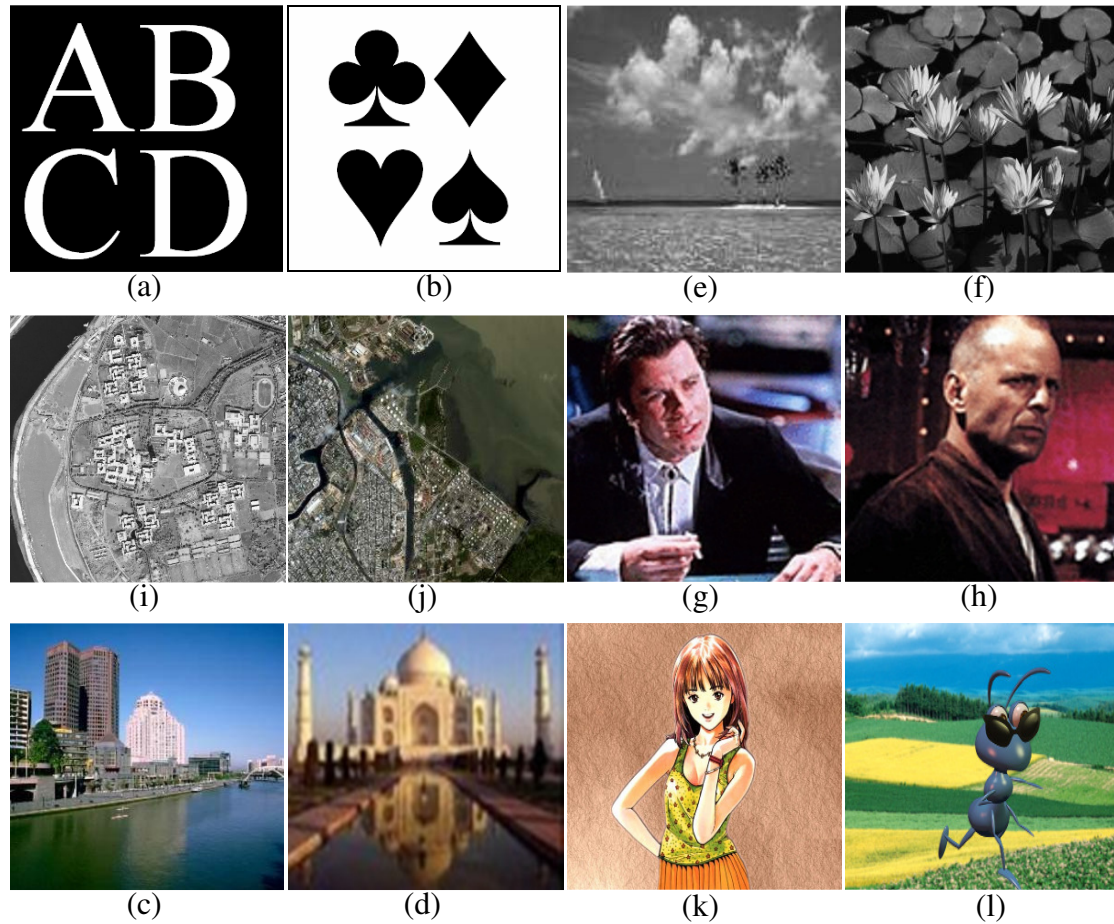


Figure 3: The test images.

9. Results and Discussion

The practical test using traditional partitioning methods showed that the kernel size may effectively change the classification results, such that it was very necessary to make the kernel size to be dynamic. This is the reason of suggesting the median based partitioning (MBP) method. In such method, the kernel size is not predefined, but it properly determined according to the details variety in the image. So that kernel size is found varies from image to another, almost takes a small size about 2-8 pixels. The true determination of kernel size makes the classification results to be more confident. Also, it was observed that true partitioning is greatly help the ACO to determine the optimal number of classes in each image, which absolutely leads to optimal classification. (Figure 4) shows the partitioning results by using the MBP method and their classification using the ACO, whereas table (1) indicates the parametric results

achieved through classifying the material images.

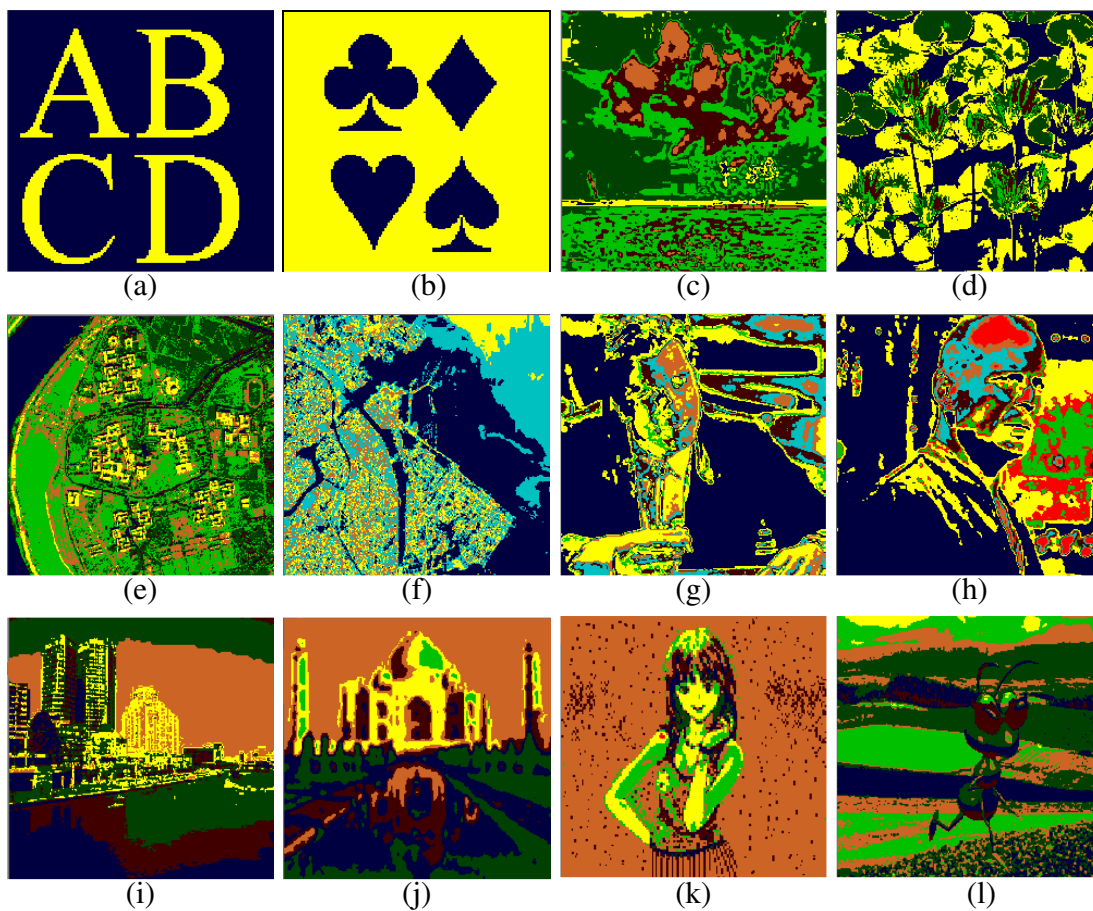


Figure 4: The classification results for the images shown in Fig (3).

Table 1: Parameter results achieved through the ACO classification.

| Image | B_s | Am | Vm | V_T | N_c |
|-------|-------|------|------|-------|-------|
| a | 6 | 106 | 4 | 255 | 2 |
| b | 6 | 112 | 4 | 255 | 2 |
| c | 6 | 134 | 10 | 173 | 5 |
| d | 5 | 152 | 8 | 195 | 4 |
| e | 4 | 157 | 10 | 80 | 5 |
| f | 4 | 129 | 8 | 224 | 4 |
| g | 5 | 98 | 14 | 196 | 7 |
| h | 5 | 124 | 12 | 217 | 6 |
| i | 4 | 107 | 12 | 196 | 6 |
| j | 5 | 112 | 10 | 221 | 5 |
| k | 6 | 197 | 12 | 183 | 6 |
| m | 5 | 162 | 16 | 151 | 8 |

10. Analytical Observation

It is observed that the proposed approach was able to find effectively the optimal solution for the images under test, a good classification results can be shown. The classification results show that the choice of fixed kernel size do not degrading the results of classification, because the kernel size was assumed to be dynamic, that means it was determined only whenever all the image kernels become spectral homogenous. Thus, the determined kernel size (B_s) was clearly shown different in table (1) from image to another, so it useful to classify the region of more fine details (such as the picture of satellite image) and also the region of fewer details (such as the smooth background).

Also, it is noticeable that ACO for image classification was successful in finding the proper number of classes in each image. The results of classifying the binary images (Figure 4-a and b) showed two classes are found in the images, the classification follow the spectral uniformity due to the image regions were homogenous. There was some confusions are occurred at the regions of edges due to the individual kernel was contains both the black and white, such that the ACO pointed to the class in terms of the dominant color. Whereas the results of the gray images (Figure 4c and d) gave a proper number of classes, it was seen that the gray images are classified according to the spectral uniformity appeared in each image. Since the images contained expanded regions of spectral homogeneity, each class was fitted to include a specific region. In comparison with the satellite images (Figure 4-e and f), one can note the number of classes was a measure for the amount of the details appeared in the image, which is in turn approaches to that of gray images. Indeed, the chromaticity do not greatly serves the classification of satellite images, so the classification found occurred just depending on the spectral variety. This refers to the differencing in the classification behavior according to the type of the image intended to be classified, which is robustness added to the ACO achievements.

The results of the discrete tone images (Figure 4-g and h) point out to the existence of greater number of classes in comparison with the continuous tone images (Figure 4-i and j), this is because the latter was composed of less chromaticity and details, which leads almost to greater description for

meant image. This ensures the accurate classification can obtained by ACO since it is related to the image decomposition in terms of spectral intensity and spectral details. Also, the results of the cartoon like images (Figure 4-k and l) were good since it gave a number of classes was equivalent to the amount of the colors exist in the image, furthermore each class was shown occupy an extended region in the image.

In general, the ACO method for classification purposes was successfully indicating actual results to classify different conceptual images, which ensure the efficiency of the employed method and the good performance of the classification.

11. 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 segmenting the image depending on the spectral uniformity, such that the kernel size found differs from image to another. The use of ACO was successfully determining the number of classes in each image, and showed an acceptable classification results. For further work, we suggest using a clustering step after the partitioning to guide the ACO into more accurate results. Also, one can use GA hybrid with ACO frequently for determining the optimal number of classes and image classification.

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