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Autonomous Agents-Based Approach for Color Image Segmentation

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Abstract: Image segmentation can be viewed as a labeling process in which image pixels are categorized into different classes that each class groups pixels sharing similar attributes. In this study, an unsupervised color image segmentation algorithm is presented using the Ant Colony System (ACS) algorithm and a Markov Random Field (MRF) segmentation model. The goal is to find a labeling, which is both piecewise smooth and consistent with the observed data image. We consider a energy function based on Markov Random Fields and we seek for the labeling that minimizes it. This is a combinatorial optimization problem difficult to solve. Ant algorithms are evolutionary algorithms where artificial ants are allowed to interact and cooperate to find the best solution to the given problem. The proposed algorithm is based on a population of simple agents, which construct candidate segmentation, by a relaxation labeling with respect to the contextual constraints. A local search is added to achieve further improvement. Experiments are performed on both synthetic and real images to compare the proposed algorithm to other metaheuristic techniques. The results show that our algorithm is quite competitive to other well known metaheuristic techniques.

Key words: Color image segmentation, MRF, ant colony optimization

INTRODUCTION

Image segmentation is a low-level image processing task in a vision system. It is a crucial ingredient for object recognition and a very difficult task to perform. Image segmentation aims at partitioning an image into regions in order that each region groups contiguous pixels sharing similar attributes (intensity, color, etc.). Color image segmentation has been receiving an increasing attention in recent years because color images contains more information than gray level and allows us to obtain more meaningful and robust segmentation. A broad range of color image segmentation methods have been proposed in the literature. They can be classified into the following categories:

- Edge based segmentation[1,2].
- Region splitting and growing based segmentation[3-7].
- Histogram based segmentation[8-10].
- Clustering based segmentation[10,11-15].
- Artificial neural network based segmentation[16].

A good review of color image segmentation methods can be found in[17] .

A classical clustering technique for color image segmentation is the C-means algorithm and its fuzzy version Fuzzy C-means. The C-means algorithm starts from a set of C reference points chosen either randomly or using a priori knowledge and representing the centroids of C clusters. Partitioning is done by assigning each pixel to the closest cluster, according to its distance to the cluster centroid in the color space. The new centroids for the obtained clusters are computed and the points are re-assigned again to their closest cluster until a termination criterion is reached. C-means algorithm has been widely used because of its simplicity and its rapid convergence. However, the C-means algorithm requires a free-noise image and a good starting partition (good initial centroids). Moreover, the C-means is a descend gradient method and so can be often trapped in a local minimum which may be far from the global minimum.

The technique discussed in this paper, is unsupervised color image classification pixel using both the color information and the spatial knowledge to assure spatial continuity, which means that the labels of a color pixel depends not only on its color but also on the labels of its neighbors color pixels. This idea is well expressed in the Markov Random Field (MRF) theory[18,19]. MRF has been shown to be quite successful for image segmentation because of its ability to characterize spatial relations among image pixels by conditional probability over small neighborhoods of pixels. Within this framework, the segmentation process is expressed as the problem of finding the optimum value of an energy function[20,21]. This is combinatorial optimization problem because of the large search space. Moreover, the energy function is usually non-convex and exhibits many local minima in the solution space. Techniques such as

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Iterated Conditional Method (ICM)[22], Simulated Annealing (SA)[19,23] and Genetic Algorithm (GA)[9] are often used.

This study describes a new effective approach for color image segmentation, following the concept of Ant Colony Optimization (ACO) metaheuristic[24]. Our main motivation is that ACO metaheuristic has been especially suited to find solutions to difficult discrete optimization problems and has been shown more adaptive and more robust against conventional global heuristics[25]. The aim of the proposed approach is to investigate the performance of the foraging model of Ant Colony System (ACS)[25], which is the best version of ant algorithms to solve the segmentation problem. Since the ACO shares the GA's attributes of flexibility, robustness and implementation ease and improves on its random behaviour, it seems a very promising for the optimisation problems like the clustering problem.

An ant colony searches collectively for a good clustering to the color image. Each individual ant constructs a candidate clustering by assigning each color pixel to the nearest cluster with respect to the contextual constraints. The best clustering representing the optimum value of an energy function, which is based on MRF, emerges from ants' cooperation. The solutions constructed by ants are improved by applying a simple local search. The method has been tested on real and synthetic images. The obtained results substantiate the feasibility of the method, whose performance is compared, for evaluation to the SA and GA heuristics.

STATEMENT OF THE PROBLEM

The MRF was introduced in image analysis by Geman and Geman[19]. MRF theory provides a tool for modeling a vision problem within the Bayes framework using spatial continuity. In MRF based approach, image segmentation is view as a labeling problem. Spatial relations within the image are included in the labeling process through statistical dependence among neighboring pixels. We present in the following a brief description of the MRF color image segmentation. Let F be the observed color image on a rectangular lattice S. Each pixel $s \in S$ is characterized by its color $f_s = (f_s^r, f_s^g, f_s^b)$ in RGB color space. Let X be the random filed representing the labeling defined on S. Realization of fields F (resp. X) will be denoted $f = \{f_s, s \in S\}$ (resp. $X = \{x_s, s \in S\}$). Let $\Lambda = \{0, \ldots L^{-1}\}$ a label set where L is the total number of the color patches in the image and Ω the set of all possible label configurations $x = \{x_s, s \in S\}$ where $x_s = l$ indicates that that the cluster label l is assigned to the pixel s. we assumed that (F, X) is a Markov Random Field on S with respect to a neighboring system, $N = \{N_s, s \in S\}$ where is the set of pixels neighboring x

We are looking for the labeling which maximizes the a posteriori probability, P (x/f) that is the Maximum A Posteriori (MAP) estimate[19] defined by:

$$\hat{x} = \arg\max_{x \in \Omega} \{P(x/f)\} = \arg\max_{x \in \Omega} \frac{P(f/x).P(x)}{P(f)} \quad (1)$$

We make the assumption that the image data are conditional independent and that F is obtained by adding an identical independently distributed (i.i.d.) Gaussian noise. We have:

$$P(f/x) = \frac{1}{(2\pi)^{(N/2)}} \mathrm{Exp}\left[-\sum_{s \in S}\left\{\frac{(f_s - \mu_{x_s})^2}{2\sigma_{x_s}^2} + \log(\sigma_{x_s})\right\}\right] \quad (2)$$

where N is the total number of pixels in S.

For each cluster k, the number of pixels in the cluster, N_k, the mean of colors of k, μ_k and the deviation of colors of k, σ_k are computed as:

$$N_k = \sum_{x_s = k} 1 \quad (3)$$

$$\mu_k = (\mu_k^r, \mu_k^g, \mu_k^b) = \left(\frac{1}{N_k}\sum_{i=0}^{N_k} f_i^r, \frac{1}{N_k}\sum_{i=0}^{N_k} f_i^g, \frac{1}{N_k}\sum_{i=0}^{N_k} f_i^b\right) \quad (4)$$

$$\sigma_k^2 = (\sigma_k^{2r}, \sigma_k^{2g}, \sigma_k^{2b}) = \left(\frac{1}{N_k}\sum_{i=0}^{N_k}(f_i^r - \mu_k^r)^2, \frac{1}{N_k}\sum_{i=0}^{N_k}(f_i^g - \mu_k^g)^2, \frac{1}{N_k}\sum_{i=0}^{N_k}(f_i^b - \mu_k^b)^2\right) \quad (5)$$

The distance between each pixel s and the center of the cluster k is defined by:

$$(f_s - \mu_k)^2 = \left((f_s^r - \mu_k^r)^2 + (f_s^g - \mu_k^g)^2 + (f_s^b - \mu_k^b)^2\right) \quad (6)$$

According to the Hammersley-Clifford theorem[22], the probability density of the prior model P (x) is given by a Gibbs distribution with respect to the neighboring system N. P (x) has de form:

$$P(x) = \frac{1}{Z}\exp\left\{-\sum_{c \in C} V_c(x)\right\} \quad (7)$$

Z is the normalization function, $V_c(x)$ is the potential function for clique c and C is the set of all cliques over the image. A clique is a set of pixels that are neighbors of one another. In this study we consider only the pair-site clique potentials of 8-neighborhood system, with the form $V(x_1, x_2) = -\beta$ if $x_1 = x_2$ and 0 otherwise. is a positive parameter and the larger , the larger is the influence of the neighboring pixels.

From Eq. 2 and Eq. 3 we have:

$$\hat{x} = \arg\max(-U(x)) \Rightarrow \hat{x} = \arg\min(U(x)) \quad (8)$$

where the energy function U (x) has the form

$$U(x) = \left\{ \sum_{s\in S} \frac{\left(f_s - \mu_{x_s}\right)^2}{2\sigma^2_{x_s}} + \sum_{s\in S} \log(\sigma_{x_s}) + \sum_{c\in C} V_c(x) \right\} \quad (9)$$

Since the energy function U is non-convex, several combinatorial optimization techniques have been proposed to solve the problem. Herein, we will use the Ant Colony System (ACS) algorithm.

ANT ALGORITHMS

Ant algorithms are simple evolutionary algorithms, which differ from other evolutionary computation techniques in that they are motivated from the simulation of social behavior. Ant algorithms are based on the foraging behavior of ant colonies concerning in particular how they can find shortest paths between food sources and their nest without using visual cues. Experiments studies[22,26-28] show that ants foraging for food lay down quantities of a volatile chemical substance named pheromone, marking their path that it follows. Ants smell pheromone and decide to follow the path with a high probability and thereby reinforce it with a further quantity of pheromone. The probability that an ant chooses a path increases with the number of ants choosing the path at previous times and with the strong of the pheromone concentration laid on it[25].

The fundamental approach of ant algorithms consists in exploiting the ability of a population of artificial ants to search for good quality solutions to discrete combinatorial optimization problems. In Ant algorithms, trial solutions are constructed incrementally based on the information contained in the environment and the solutions are improved by modifying the environment via a form of the pheromone trails.

Ant is defined as a simple agent, which repeatedly constructs a candidate solution by adding components to a partial solution. Partial solutions are seen as the states and the ant moves from one state to another to a more complete partial solution according to a probabilistic state transition rule. The state transition rule depends on an artificial pheromone trail t representing experience gathered by ants in previous iteration and a heuristic information h that represent a priori information of the given problem. Once all ants have built a solution, pheromone trails are updated and the amount of pheromone deposited is a function of the quality of the solution constructed. The goal of this update process is the increasing the probability of choosing the moves that were part of good solutions, while decreasing all others.

Ant algorithms have been applied successfully to various combinatorial optimization problems like the Traveling Salesman Problem (TSP)[25,29], the quadratic assignment[30,31] or graph-coloring[32]. A good review of these algorithms can be found in[25].

Recently ant algorithms have been used to solve the clustering problem. The first ant based clustering algorithm is attribute to Deneubourg *et al.*,[27]. They discovered that works ants exhibits clustering behavior based on the cemetery organization. The works ants collect their dead and form piles of corpses to clean up their nests and form cemeteries. Form this study, a mathematical model has been derived and applied in robotics and extended by[33,34] to deal with numerical data analysis. In the image processing domain, Ramos *et al.*,[35] were inspired by ant behavior to detect outlines and Ouadfel *et al.*,[36,37] applied the ant approach for image segmentation.

In[37] an hybrid Ant Colony System has been used for MRF based image segmentation. ACS is one of the best ant algorithms[25] that introduced a particular use of pheromone trails and a new state transition rule. Several ants of a colony compete to label image pixels. After a number of iterations, the best labeling, which represents the optimum value of the posterior energy function emerges. In this study, we extend[37] to deal with color image segmentation.

APPLYING ACS FOR THE COLOR IMAGE SEGMENTATION

Our ant algorithm is a transposition of the ACS algorithm for color image segmentation. Ants construct candidate clustering for image pixels and apply local search to achieve further improvement. Candidate clustering xcandidate is defined by the set of pairs (s, l) representing the assignement of cluster label l to pixel s:

$$x_{candidate} = \{(s,l),\ s \in S \text{ and } l \in \Lambda\} \quad (10)$$

Informally our ant algorithm works as follows: K artificial ants explore in parallel a discrete grid representing the image. Ants are initially scattered randomly on the grid and move from pixel to another until all pixels have been assigned to clusters. The construction of a labeling involves two steps. First, a pixel has to be chosen and next the pixel has to be assigned to a cluster. The next pixel is chosen randomly from the set of pixels not yet treated.

For the second step, we use the pheromone trails τ (s,l) referring to the desire of setting $x_s = l$ in the ant' solution and made available by previous attempts of other ants. The artificial pheromone trail is numeric information encoded as a matrix of dimension (N, L) where N is the number of image pixels and L is the total number of the pattern clusters in the image. Each ant builds incrementally a possible labeling of image pixels with respect to the contextual constrains by repeatedly applying a stochastic rule. Once an ant k has built its solution, x^k it modifies the amount of pheromones on the pairs (s, l) belonging to x^k by applying a local updating rule. Once all ants have built their solutions, each ant is brought to a local minimum using a local search method in order to enhance the quality of its solution found during the search process.

Finally, at the end of the iteration, the amount of pheromone is updated again by a global updating rule according to the quality of the best solution found from the beginning of the labeling process. The algorithm stop iterating when a maximum of number of iterations has been performed.

The proposed algorithm proceeds as follows:

- Initially, assign each couple (s, l) with a fixed pheromone τ0;
- Each ant explores the grid-image to create a feasible labeling xi for image pixels, where i = 1,…,K;
- Apply a local pheromone updating rule according to Eq. 15;
- Locally improve the K solutions;
- Evaluate all the K solutions by Eq. 9. Among all solutions, record the best solution xgb which is the global best labeling since the beginning of the program;
- Update the pheromone for each couple (s, l) belonging to xgb using Eq. 13 and 14;
- If the maximum iterations are reached, stop and report the best labeling xgb found. Otherwise go to step 2.

In the following we present into details our implementation of our algorithm, step by step.

Initial value of τ0: Initially, all the traces are set to the same value t_0 $\tau(s,l) := \forall s \in S,\ l \in \Lambda$

Building a feasible clustering: Each ant builds a candidate clustering step by step by choosing the hypothetical assignments (s,l). The choice of assigning a cluster label l to a pixel s is done according to ACS state transition rule. There are two ways of using this transition rule[25]: exploitation and exploration. Exploitation exploits the knowledge available about the problem by choosing for a pixel s the cluster label l that maximizes the amount of the pheromone trails. Exploration is a stochastic process in which a cluster label is assigned to a pixel in a probabilistic way. Therefore, with probability q0 an ant assigns a cluster label l to a pixel s with a maximum τ (s,l);

$$l = \arg\max_{u \in \Lambda} \tau(s,u) \quad (11)$$

Otherwise a random decision is made in which a cluster label l = 1,… ,L is chosen with probability.

$$P(s,l) = \frac{\tau(s,l)}{\sum_{u \in \Lambda} \tau(s,u)} \quad (12)$$

Parameter q0 controls the importance of the exploitation versus exploration. We can interpret the ant colony as a reinforcement learning system, in which reinforcements (the pheromone trails) modify the strength of assignment pixel-label. In Eq. 11 an ant exploit with probability q0 the experience accumulated by the ant colony in the form of pheromone trail (pheromone trail will tend to grow on assignments (s,l) which belong to the best clustering, making them more desirable). In Eq. 12 the ant apply with probability (1-q0) a biased exploration of new assignment by choosing a label to assign to a pixel randomly, with a probability distribution that is a function of the pheromone trail accumulated by ants.

Local updating rule: Once an ant has built a partition, it updates the pheromone trail values of the corresponding pairs (s,l) according to the local updating rule as follows:

$$t(s,l) = (1-?)t(s,l) + ?t_0 \quad (13)$$

Where ρ is a parameter in]0,1[, which represents the local pheromone decay parameter and τ0 is the initial pheromone value.

Improving solutions by local search : Local search has shown to be effective to solve large optimization problems. The basic idea is to construct a complete labeling and then iteratively refine it by changing some pixel-label assignment. Ant algorithms and therefore also our algorithm are solution construction heuristics, which after each iteration produces a set of feasible solutions. Adding a local search yields a faster convergence of the algorithm and an earlier detection of high quality solutions. During each iteration, ants construct labelings, using pheromone trails and local search improves their quality by iteratively performing local moves. We propose to combine local search with our algorithm in order to guide it toward the most promising area of the search space when constructing new solutions.

The local search algorithm used is presented in Fig. 1. For each ant solution, we use a simple iterative improvement local search that starting from an initial solution iteratively replaces the current solution by a better solution in its neighborhood. The neighborhood for a current clustering $x \in X$ is the set of candidate clustering $N(x) \subset X$ that can be reached from x by making small modifications on the membership of pixels $s \in S$.

Iterative improvement has been implemented using the first improvement, i.e., the first improving move found is accepted. With the first improvement strategy the examination of the whole neighborhood that may be rather expensive is avoided. For each solution x, we evaluate the neighboring candidates solutions and the first x' for which, ie. the first improving neighbor encountered, is selected. The neighborhood of a solution is defined by a set of solutions that can be obtained by exchanging the class labels of two pixels[37].

```
Let x ∈ X the segmentation to improve
Let w = ϕ
WHILE (N (x)/w ≠ ϕ) DO
        X = Generate Solution (x)
        IF U (x`) < U (x) THEN Return x`
        ELSE     W = w ∪x`
    END-WHILE
   Return    X
```

Fig. 1: The local search algorithm

Record the best solution: In this step, we evaluate each solution xk described by the k-th ant according to Eq.9. We record the global best solution $x^{gb} = \min_{k=1,\dots,K} (U(x^k))$ found since the beginning of the algorithm.

Global pheromone trail updating rule: As in ACS, only the globally best ant, the one that constructed the clustering with the minimum energy function defined in Eq. 9 from the beginning of the algorithm, is allowed to update the pheromone trails. This update is intended to make the search more directed by forcing ants to search in a neighborhood of the best solution found. The pheromone trails are updated according to the following global updating rule.

$$\tau(s, l) = (1-\alpha).\tau(s, l) + \alpha.\Delta\tau(s, l) \tag{14}$$

where

$$\Delta\tau(s, l) = \begin{cases} \dfrac{1}{U(x^{gb})} & \text{if } (s, l) \in x^{gb} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

$0 < \alpha < 1$ is a global pheromone decay parameter.

EXPERIMENTAL RESULTS

The algorithm proposed in this paper was coded in Borland C++ and tested on Pentium 700 MHz PC. The computational testing of the new algorithm was carried out applying the code to a variety of images including synthetic noisy images and real color images. This section described the results of our experiments. First the different parameter values are fixed, then the results are compared to two of the best performing metaheuristics so far proposed for the clustering problem, lamely simulated annealing and genetic algorithm with the parameters presented in[37].

In order to identify a good parameter setting, we performed several simulations, testing the algorithm on different images with various values of the control parameters.

In Fig. 2 we show the images chosen for the purpose of setting the algorithm parameters. They are three color images of dimensions 256*256.

The first parameter to define was the number K of ants. To shoes its value we run tests with a fixed values of other parameters but different number of ants. The number of ants K is set to ten for which good solutions were found for all the tests. With greater values, running times increase while solutions are not improved.

Parameters α and ρ determine pheromone evaporation and have an influence on the exploratory behavior of ants. Higher values reduce the persistence of the pheromone and the algorithm's efficiency: it takes longer to find good solutions; the best results were obtained for $\alpha = \rho = 0.1$.

For the initial value of the pheromone trails $\tau 0$, it was experimentally found that setting, $\tau_0 = 1/(n.U(x^0))$ where x0 is an initial solution created by a greedy heuristic[22] produces good results.

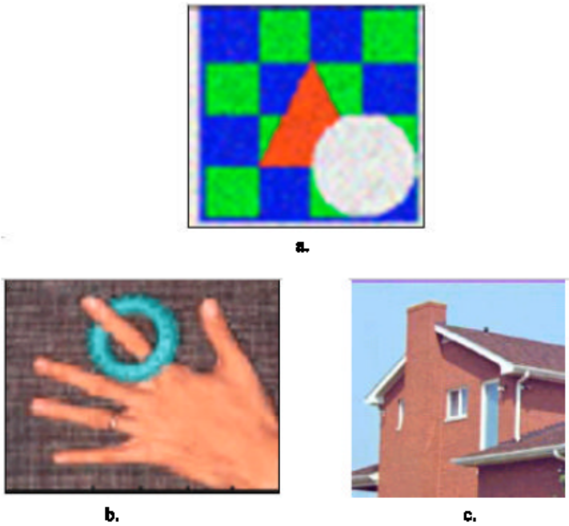

Fig. 2: Test images : a. Noisy synthetic image (SNR = 5db) with 4 classes, b. . Original color image with 3 classes, c. Original color image with 3 classes.

Table 1: Measures comparison for synthetic image

		SA results	GA results	Our results
Jaccard	1	0.96	0.97	0.98
similarity	2	0.97	0.98	0.98
for	3	0.97	0.98	0.99
clusters	4	0.98	0.98	0.99
Borsotti *et al.*, Measure (Q)		9.055	8.590	8.588

Table 2: Borsotti *et al.*, Measure (Q) comparison for real color images (a) and (b).

	(a)	(b)
SA results	1.120	0.905
GA results	1.1029	0.855
Our results	1.103	0.850

Tuning q0 allows to modulate the degree of exploration ($q_0 \approx 0$) versus exploitation ($q_0 \approx 1$) and to choose whether to concentrate the search of the algorithm on the best solutions (greedy search) or to explore the search space. The importance of the value of parameter q0 was tested by running different experiments and was fixed to ($q_0 = 0.9$) .

The clustering results of the different algorithms on the test images are compared using two different evaluation measures. The first measure makes use of the correct clustering known only for the synthetic images for which we have the ground truth.

- The Jaccard similarity measures the similarity of two sets as the ration of the size of their intersection divided by the size of their union. Let and denotes the total number of pixels labeled into a cluster k in the ground truth (g) and the obtained segmentation (s). For cluster k the Jaccard similarity is defined by

$$J^k(g,s) = \frac{\left|V_g^k \cap V_s^k\right|}{\left|V_g^k \cup V_s^k\right|} \quad (16)$$

A good segmentation is obtained when $J^k(g,s)$ is near 1 which means that the cluster k is well detected.

- The Borsotti-measure: Based on the evaluation function defined by Liu *et al.*,[23] Borsotti *et al.*,[38] proposed the following evaluation function of a segmentation result without need to a ground truth.

$$Q(I) = \frac{1}{1000(N*M)}\sqrt{R}\sum_{k=1}^{R}\left[\frac{e_k^2}{1+\log A_k} + \left(\frac{R(A_k)}{A_k}\right)^2\right] \quad (17)$$

where: I is the segmented image, N*M, size of the image, R, the number of regions in the segmented image, A_k the area of pixels of the K^{th} region, R(A) is the number of regions with area equal to A and ek the color error of region k. The color error in RGB space is calculated as sum of the square of the Euclidean distances between the color vectors of the pixels in region k and the average color vector attribute to region k in the segmented image.

$$e_k = \left(\sum_{i=0}^{N_k}\sqrt{\left(f_i^r - \mu_k^r\right)^2 + \left(f_i^g - \mu_k^g\right)^2 + \left(f_i^b - \mu_k^b\right)^2}\right) \quad (18)$$

The first term of Eq. 17 is a normalization factor, the second term penalizes results with too many regions and the third term penalizes simultaneously regions with big color error and small regions. The smallest the value of Q(I), the better the segmentation results.

Figure. 2 shows the test images used to evaluate the performance of the proposed algorithm. The images used are RGB color images

Table 1 and 2 list evaluation values of the segmentation results of the three test images obtained with our algorithm (applied 2000 times), SA(applied 2000 times) and GA (applied 1000 times) algorithms. Only the best values of Jaccard similarity and Borsotti-measure are reported over 10 test runs for each method.

Results show that ACS performs well, as good as GA and better that SA .

CONCLUSION

In this paper, we introduce a new ant-based algorithm for color image segmentation. The segmentation model is defined in a Markovian Framework and uses Ant Colony System algorithm in order to tie the final segmentation to the observed image. Artificial ants cooperate to find the best labeling to image pixels.

The stochastic clustering is biased by the pheromone trail, which represents the learned desirability of an assignment. A local improvement of created solution yields a faster convergence of the algorithm and an earlier detection of high quality solutions.

The proposed algorithm was numerically tested for its effectiveness and has shown that it performed best than other methods.

REFERENCES

1. Chapron, M., 1997. "A chromatic contour detector based on abrupt change techniques" Int'l Conf. On Image Processing (ICIP'97), Santa Barbara, CA, 26-29 October., pp: 18-21.
2. Tao, H. and T.S. Huang, 1997. "Color image edge detection using uluster analyis", Proc. of Int'l Conf. on Image Processing (ICIP'97), Santa Barbara, CA, pp: 834-836.
3. Cramariuc, B., M. Gabbouj and J. Astola, 1997. "Clustering based region growing algorithm for color image segmentation", Proc. of the 13th Intl Conf. on Digital Signal Processing, Santorini, Greece, pp: 857-860.
4. Gevers, T. and V.K. Kajcovski, 1994. "Image segmentation by directed region subdivision", Proc. of the 12th Int'l Conf. on Pattern Recognition, Jerusalem, pp: 342-346.
5. Itoh, S. and I. Matsuda, 1996. "Segmentation of colour still images using voronoi diagrams", Proc. of the 8th European Signal Processing Conference (EUSIPCO-96), Trieste, Italy, 10-13 Sept., pp: 1869-1872.
6. Trémeau, A. and P. Colantoni, 2000. "Region adjacency graph applied to color image segmentation", IEEE Trans. on Image Processing, pp: 735-744.
7. Tremeau, A. and N. Borel, 1997. "A region growing and merging algorithm to color segmentation", Pattern Recognition, 30: 7, pp: 1191-1203.
8. Celenk, M. and Uijt de Haag, 1998, "Optimal thresholding for color images", Proc. of the SPIE - The Int'l Soc. For Optical Eng., Nonlinear Image Processing IX, San Cose,CA, Jan., pp: 250-259.
9. Bonabeau, E., M. Dorigo and G. Therualez, 1999. "Swarm Intelligence: From Natural to Artificial Systems", New Work: Oxford University Press.
10. Vandenbroucke, N., 2000. "Segmentation d'images couleur par classification de pixels dans des espaces d'attributs colorimétriques adaptés-Application à l'analyse d'images de football", Thèse de doctorat, Université des Sciences et Technologies de Lille.
11. Fontaine M., L. Macaire and J.G. Postaire, 2000. "Color image segmentation based on a multiscale analysis of pixel connectivity properties", In CGIP'2000 : 1st Int. Conf. on Color in Graphics and Image Processing,Saint-Etienne, France. pages 78-83,
12. Liew A.W.C., S.H. Leung and W.H. Lau, 2000. Fuzzy image clustering incorporating spatial continuity, IEEE Proceedings on Vision Image Signal Processing, pp: 185-192.
13. Miyakoshi Y.M. and M. Shimbo, 1994. "A fuzzy clustering method for automatic segmentation of color scenes", Jap. J. of fuzzy Theory and systems., 6, pp: 651-672.
14. Moghaddamzadeh A. and N. Bourbakis, 1997. "A fuzzy region growing approach for segmentation of color images", Pattern Recognition, 30: 867-881.
15. Weeks, A.R. and G.E. Hague, 1997. "Color segmentation in the HSI color space using the k-means algorithm", Proc. Of the SPIE - Nonlinear Image Processing VIII, San Jose, CA, pp: 143-154.
16. Campadelli P., D. Medici and R. Schettini, 1997. "Color image segmentation using uopfield networks", Image and Vision Computing Image, 3: 161-166.
17. Cheng, H.D., X.H. Jiang, Y. Sun and J. Wang, 2001. "Color image segmentation: advances and prospects", Pattern Recognition, 34: 2259-2281.
18. Dubes, R., S. Nadabar, C.C. Chen and A.K. Jain, 1990. "MRF Model-Based algorithm for Image Segmentation" Proc. 10th Intl. Conference on Pattern Recognition, Atlantic City, pp: 808-814.
19. Geman, S. and D. Geman, 1984. "Stochastic relaxation, Gibbs distribution and Bayesian restoration of images", IEEE Trans. Pattern Anal. Machine Intel. pp: 721–741.
20. Li, S.Z., 1995. "Markov random field modeling in computer vision", Springer ed., Tokyo.
21. Besag J., 1986, "On the statistical analysis of dirty pictures", J. Roy. Statist. Soc. B 3: 259-302.
22. Panjwani, D.K. and G. Healey, 1995. "Markov random field models for unsupervised segmentation of textured color images", IEEE Trans. Pattern Anal. Machine Intell. 10: 939-954.
23. Liu, Y.H., 1994. "Multiresolution color image segmentation techniques", IEEE.Trans. On Pattern Analysis and Machine Intelligence, 16: 689-700.
24. Dorigo, M., G. Di Caro and L. Gambardella, 1999. "Ant algorithms for discrete optimization", Artificial Life. 2: 137-172.

25. Dorigo, M. and L. Gambardella, 1997. "Ant colony system: a cooperative learning approach to the traveling salesman problem", IEEE Transactions on Evolutionary Computation, pp: 53-66.
26. Deneubourg, J.L. and S. Goss, 1989. "Collective patterns and decision-making", Ethology and Evolution, pp: 395-311.
27. Deneubourg, J.L., S. Goss, N. Franks, A. Sendova-Franks, C. Detrain and L. Chretien, 1991. "The Dynamics of Collective Sorting Robot-like Ants and Ant-like Robots", In "Fromanimals to Animats", Mit Press, Pp: 356.
28. Dorigo, M., V. Maniezzo and A. Colorni, 1991. "Positive feed back as a search strategy", Technical Report (16). Politecnico di Milano, Italy.
29. Dorigo, M. and M. Gambardella, 1997. "Ant Colony for the traveling salesman problem", Biosystems, pp: 73-81.
30. Maniezzo, V., A. Colorni and M. Dorigo, 1994. "The Ant System Applied to the Quadratic Assignment Problem", Technical Report. IRIDIA. (28), Université Libre de Bruxelles, Belgium.
31. Taillard, E. and L. Gambardella, 1997. "An Ant approach for structured quadratic assignment Problems", 2nd Metaheuristic International Conference (Mic-97), Sophia-antipolis, France.
32. Costa. D. and A. Hertz, 1997. "Ants Can Color Graphs", J. the Operational Res. Soc., pp: 295-305.
33. Lumer, E. and B. Faieta, 1994. "Diversity and adaptation in populations of clustering ants", In Proc. of the Third International Conference on Simulation of Adaptive Behavior: from animals to animats 3, , Cambridge, Massachusetts MIT press.,pp: 499-508.
34. Monmarche, N., M. Silmane and G. Venturini, 1999. "AntClass: discovery of clusters in numeric data by an hybridization of an ant colony with k-means algorithm", Internal Report no. 213, Laboratoire d'Informatique de l'Universite de Tours, January 1999.
35. Ramos, V. and J.J. Merelo, 2002. "Self-Organized stigmergic", Document Maps: Environment as a Mechanism for Context Learning, in AEB´2002 – 1st Spanish Conference on Evolutionary and Bio-pInspired Algorithms, E. Alba, F. Herrera, J.J. Merelo *et al.*, (Eds.), Centro Univ. de Mérida, Mérida, Spain, pp: 284-293,
36. Ouadfel, S. and M. Batouche, 2003. "Ant Colony System with local search for Markov Random Field Image Segmentation", Proceedings of the International Conference on Image Processing, (ICIP) 2003, pp: 133-136.
37. Ouadfel, S. and M. Batouche, 2003. "MRF-based image segmentation using Ant Colony System", Electronic Letters on Computer Vision and Image Analysis, pp: 12-24.
38. Borsotti, M., P. Campadelli and R. Shettini, 1998. "Quantitative evaluation of color image segmentation results", Pattern Recognition letters pp: 741-747.