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Interactive Image Segmentation Using Combined MRF and Ant Colony Optimization

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Abstract: Image segmentation is the process that partitions an image into region. Although many literatures studied automated image segmentation, it is still difficult to segment region-of-interest in any kind of images. Thus, manual delineation is important yet. [2] In order to shorten the processing time and to decrease the effort of users, this paper introduces the approaches of interactive image segmentation method based on MRF and Ant colony optimization. In this paper we proposed a segmentation algorithm combined MRF with ACS, which not only applied ACS as optimization algorithm but also introduced the neighborhood pheromone interaction rules into ACS under MRF model. Interactive segmentation aims to separate an object of interest from the rest of an image. This problem in computer vision is known to be hard, and very few fully automatic vision systems exist which have been shown to be accurate and robust under all sorts of challenging inputs. Most of the previous works require users to trace the whole boundary of the object. When the object has a complicated boundary, or the object is in a highly textured region, users have to put great effort into iteratively correcting the selection. [1] Dirichlet Process Multiple-View Learning (DPMVL) for image segmentation technique produces very effective segmentation results as compare to previously existing techniques. DPMVL use MRF model for smoothing the segmentation. This can be further improved by using MRF-based image segmentation using Ant Colony System which works effectively and provide an alternative computational algorithm for building interactive image editing tools. In this paper, we present an interactive segmentation framework that integrates image appearance and boundary constraints in a principled way using combined MRF and ant colony optimization. We have improved proposed technique by using modified technology which have more interactivity, user control of segmentation process, and reach a satisfied result among the noise restraint, edge preservation and computation complexity. Experimental results are provided to demonstrate the superior performance of the proposed approach. A comparison with other standard operators is also discussed and the proposed method produced acceptable results within reasonable amounts of time. It is shown that the proposed algorithm based on ant colony optimization and MRF achieves better performance compared to the typical interactive image segmentation methods without using ant colony optimization concept.

Keywords: Image Processing, Image segmentation, Interactive image segmentation, DPMVL, MRF, Ant colony optimization.

1. Introduction

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal pro-cessing methods to them.

Image Enhancement : The principal objective of image enhancement is to process a given image so that the result is more suitable than the original image for a specific application.

Image Restoration : The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera misfocus.

Image Compression : Image compression is an application of data compression that encodes the original image with few bits. The objective of image compression is to reduce the redundancy of the image and to store or transmit data in an efficient form.

Image Segmentation : The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application.

1.1 Image segmentation

The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application. Image segmentation is a low level image processing task that aims at partitioning an image into regions in order that each region groups contiguous pixels sharing similar attributes (intensity, color etc.). It is very important process because it is the first step of the image understanding process, and all other steps such as feature extraction, classification and recognition, depend heavily on its results. Image segmentation is a low level image processing task in image applications such as machine vision and robot navigation. Recently automated image segmentation techniques with computer are adopted for improving throughput, reducing cost, diminishing human bias and increasing the intelligence level of robot. However, today computer-assisted IR image segmentation techniques have not been successfully operated for many reasons. Especially the limited resolution and electronic noise of sensors reduce qualities of images, and the interactive heat environments increase the complexities of identification [3].

The Segmentation of an image entails the division or separation of the image into regions of similar attribute. The ultimate aim in a large number of image processing applications is to extract important features from the image data, from which a description, interpretation, or under-standing of the scene can be provided by the machine. [4] Numerous methods have been proposed for image segmentation such as histogram-based method, boundary-based method, region-based method and graph-based techniques. [5]

1.2 Interactive Image Segmentation

Interactive figure-ground segmentation is an important problem in computer vision and image processing. Given some user input, which typically takes the form of marking some pixels that belong to the figure or background, the system is required to find the set of pixels that belong to the figure. Like many other image labeling problems, interactive segmentation is commonly modeled using pair wise Markov Random fields that incorporate priors on labels of pairs of neighboring pixels.The problem of image segmentation has received a lot of attention since the early days of computer vision research. Automatic image segmentation is a hard problem which requires modeling the problem based on do-main knowledge. And even after that, some form of human intervention is required to correct anomalies in the segmen-tation. Moreover, automatic segmentation methods are not generic. A slightly easier and more approachable problem, interactive image segmentation has also received a lot of attention over the years.

Interactive image segmentation is the process of extracting an object in an image with additional hints from the user. This problem in computer vision is known to be hard, and very few fully automatic vision systems exist which have been shown to be an ill-posed problem due to the fact that there is (i) no clear definition of a correct segmentation; and (ii) no agreed-upon objective measure that defines the goodness of a segment. For this reason a number of interactive systems have been developed which allowed users to help the vision algorithm to achieve the correct solution by giving hints [1]. Interactive segmentation aims to separate an object of interest from the rest of an image. It is a classification problem where each pixel is assigned one of two labels: foreground (F) or background (B). The interaction comes in the form of sets of pixels marked by the user by help of brushes to belong either to foreground (F) or background (B). [1]

Image segmentation is one of the fundamental but challenging problems in image processing and computer vision. The approaches of unsupervised image segmentation automatically partition an image into coherent regions with-out any prior knowledge, such as the stochastic clustering, mean shift, mixture model, level sets, and graph theoretic methods. Unsupervised image segmentation is widely used as a crucial function of high-level image understanding, which is designed to simulate functionalities of human visual perception, such as object recognition and scene parsing. However, the state-of-the-art automatic segmentation methods are still far from the human segmentation performance, which have several problems such as finding the faint object boundaries and separating objects from the complicated background in natural images. In order to solve these problems, an interactive segmentation method is often preferred when the interest objects need to be accurately selected and extracted from the background. The general task of interactive segmentation is to produce a binary segmentation mask of the input image by separating the interest objects from its background. There are a plenty of literature on the work of interactive image segmentation techniques that have been explored during the last decade, of which popular graph-based approaches include interactive graph cut , random walk , geodesic distance , and level sets. [6]

1.3 MRF-based image segmentation

A common strategy for segmenting digital imagery is using Bayesian estimation to obtain the maximum a posterior (MAP) segmentation, which based on a casual conditional characterization of Markov Random Field (MRF). The objective of this algorithm is to determine recursively the a posteriori distribution and access subsequently a Bayesian estimation of pixel intensity at each pixel given the whole image. By modeling image as an MRF, each given pixel depends statistically on the rest of the image only through a selected group of neighbourhoods, which avoid the difficult problem of assigning a meaningful prior distribution and only depend on the local conditional possibilities.[3]

MRF- based image segmentation method is a process of seeking the optimal labelling of the image pixels. A labelling process consists of accurately labelling the image pixels with a group of given labels. A label set represents the pattern classes in the image. Through a process based on local interactions among pixels, MRF allows the label selections of a pixel to be conditioned explicitly on the local interaction between the pixel and its neighbours within a well-defined neighbourhood system without involving all the pixels of the image. The image is segmented by maximizing the a posteriori probability (MAP) of the labelling space given the image data. The MRF-MAP framework involves solving an energy maximization (or minimization) problem. However this maximization is combinatorial and the energy function is usually non convex and may exhibits many local minima in the solution space. The often used methods for solving such combinatorial problem are the iterated conditional method (ICM), the simulated annealing (SA) and the genetic algo-rithm (GA).

Image segmentation algorithm based on MRF has been introduced into many application fields since Geman [18] proposed in 1984. Although this method could obtain the global optimal resolution, yet the calculation complexity of optimization is unacceptable in most of real-time image process systems. To reduce computation time consumption, many optimization algorithms are applied in this method, such as the Simulated Annealing (SA), Genetic Algorithms (GA), Immune Strategy (IS) and Evolutionary Programming (EP).[3]

Markov random field (MRF) models have been widely applied to various problems arising in digital image processing, such as image reconstruction, restoration and segmentation. In order to extract the intrinsic characteristics of the image pattern, model parameters are needed to be estimated so as to represent the pattern effectively. However, optimal estimation of these parameters from one or more realizations of the MRF is often difficult in practice. Many techniques have been presented to estimate the MRF parameters, such as the iterated conditional estimation, least-squares, and Markov chain Monte Carlo (MCMC). [17]

1.4 Ant Colony Optimization

Ant Colony Optimization (ACO) metaheuristic is a recent population-based approach inspired by the observation of real ants colony and based upon their collective foraging behavior. In ACO, solutions of the problem are constructed within a stochastic iterative process, by adding solution components to partial solutions. Each individual ant constructs a part of the solution using an artificial pheromone, which reflects its experience accumulated while solving the problem, and heuristic information dependent on the problem. In this paper, we applied the concept of ACO for discrete optimization in MRF-based image segmentation. Our main motivation is that ACO metaheuristic has been successfully applied to several NP-hard combinatorial optimization problems and has been shown to be competitive against conventional optimization methods like GA and SA. In this paper, we will use the algorithm which uses both ACS with MRF in which a colony of artificial ant searches for an optimal labeling of image pixels that maximizes the MAP estimate. Individual ant constructs a candidate partition, by a relaxation labeling with respect to the contextual constraints. After some iteration, the partition representing the optimum value of the energy function is obtained. [19]

Ant Colony Optimization (ACO) is a population-based approach first designed by Marco Dorigo and co-workers and inspired by the foraging behavior of ant colonies. Individual ants are simple insects with limited memory and capable of performing simple actions. However, the collec-tive behavior of ants provides intelligent solutions to prob-lems such as finding the shortest paths from the nest to a food source. 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 strength of the pheromone concentration laid on it. This concept has been applied to hard combinatorial optimization problems by creating a population of artificial ants that searches for optimal solutions according to the problem's constraints. In the ACO metaheuristic, artificial ants are defined as simple agents that repeatedly construct candidate solutions by adding components to partial solutions. Partial solutions are seen as the states of the construction process and the ant moves from one state to another until a complete solution is built. Each ant moving from state i to the state j is probabilistically guided by two measures : an artificial pheromone trail $\tau(i,j)$ representing experience gathered by ants in previous iteration when choosing this move and a heuristic information $\eta(i,j)$ that represents a priori information of the given problem. Each ant updates pheromone trails after having construct a complete solution 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.

ACO algorithm is inspired by studies and researches on ant colonies. Studies show that ants are social insects which live in colonies, and tend to survive the colony rather than surviving individuals. One of the most amazing behaviors about ants is how they find food and especially how they find the shortest path between the food source and the nest. This behavior is a kind of mass intelligence (using different intelligent agent) which has recently been the matter of interest to scientists. Ants deposit a special chemical substance named pheromone on their way to find food. The amount of pheromone depends on the length of the path and the quality of the food. Other ants smell the pheromone and are attracted by this path and they also amplify the pheromone on this path. Shorter paths get more pheromone and so, the more pheromone there is, the more ants tend to pass along the path. Thus the shortest paths are chosen by ants. Although the pheromone evaporates in a short time, it remains as an ant's trace for a limited time. Ants' movement is based on a simple instinctive behavior. They choose the path which has more pheromone or in other words, they choose the path from which more ants have passed. The important point is that, although choosing the path with more pheromone is more probable, it is not deterministic. So probability and stochasticity play an important role in ant colony algorithm. Another point is the evaporation of pheromone left on the path. By passing time, more pheromone evaporates and probability of choosing a certain path is decreased. Actually ant colony algorithm is a heuristic method for solving problems through making a graph. A lot of ants start to move on the problem solution space and each individual plays its small part to solve the problem. Choosing a direction by an ant depends on the amount of pheromone on the path and also the heuristic function.[20]

1.5 Dirichlet Process

The Dirichlet Process Provides a Random Distribution

over Infinite Sample Spaces Recall that the Dirichlet distribution is a probability distribution over pmfs, and we can say a random pmf has a Dirichlet distribution with parameter α. A random pmf is like a bag full of dice, and a realization from the Dirichlet gives us a specific die. The Dirichlet distribution is limited in that it assumes a finite set of events. In the dice analogy, this means that the dice must have a finite number of faces. The Dirichlet process enables us work with an infinite set of events, and hence to model probability distributions over infinite sample spaces.

As another analogy, imagine that we stop someone on the street and ask them for their favorite color. We might limit their choices to black, pink, blue, green, orange, white. An individual might provide a different answer depending on his mood, and you could model the probability that he chooses each of these colors as a pmf. Thus, we are modeling each person as a pmf over the six colors, and we can think of each person's pmf over colors as a realization of a draw from a Dirichlet distribution over the set of six colors. But what if we didn't force people to choose one of those six colors? What if they could name any color they wanted? There are an infinite number of colors they could name. To model the individuals' pmfs (of infinite length), we need a distribution over distributions over an infinite sample space. One solution is the Dirichlet process, which is a random distribution whose realizations are distributions over an arbitrary (possibly infinite) sample spaceyou submit your paper print it in two-column format, including figures and tables. In addition, designate one author as the "corresponding author". This is the author to whom proofs of the paper will be sent. Proofs are sent to the corresponding author only.

2. Related Work

Several methods have been proposed for Interactive image segmentation. Interactive image segmentation techniques are semiautomatic image processing approaches. They are used to track object boundaries and/or propogate labels to other regions by following user guidance so that heterogeneous regions in one image can be separated. User interactions provide the high level information indicating the "object" and "background" regions. Then, various features such as locations, color intensities, local gradients can be extracted and used to provide the information to separate desired ob-jects from the background. [11] A variety of approaches have been developed for solving image segmentation problems. In these approaches, different techniques have defined various cost functions for the task of image segmentation. There are many techniques used for interactive image segmentation.

2.1 Adaptive GMMRF model

Adaptive GMMRF model is represented by the Graph Cut algorithm of Boykov and Jolly (ICCV 2001).The problem of interactive foreground/background segmentation in still images is of great practical importance in image editing. Its underlying model uses both colour and contrast information, together with a strong prior for region coherence. Estimation is performed by solving a graph cut problem for which very efficient algorithms have recently been developed. However the model depends on parameters which must be set by hand and the aim of this work is for those constants to be learned from image data. First, a generative, probabilistic formulation of the model is set out in terms of a "Gaussian Mixture Markov Random Field" (GMMRF). Secondly, a pseudolikelihood algorithm is derived which jointly learns the colour mixture and coherence parameters for foreground and background respectively. The graph cut algorithm, using the learned parameters, generates good object segmentations with little interaction. However , pseudolikelihood learning proves to be frail, which limits the complexity of usable models and hence also the achievable error rate. [8]

2.2 Maximal similarity based region merging

This represents a new region merging based interactive image segmentation method. This is because the initially segmented small regions of the desired object often vary a lot in size and shape. In the interactive image segmentation, the users will mark some regions as object and background re-gions. The users only need to roughly indicate the location and region of the object and background by using strokes, which are called markers. A novel maximal-similarity based region merging mechanism is proposed to guide the merging process with the help of markers. A region R is merged with its adjacent region Q if Q has the highest similarity with Q among all Q's adjacent regions. The region merging process is adaptive to the image content and it does not need to set the similarity threshold in advance. [9]

2.3 Probabilistic hypergraphs

This introduces a novel interactive framework for segmenting images using probabilistic hypergraphs which model the spatial and appearance relations among image pixels. The probabilistic hypergraphs provides us a means to pose image segmentation as a machine learning problem. In particular, this assume that a small set of pixels, are labeled as the object and background. The seed pixels are used to estimate the labels of the unlabeled pixels by learning on a hypergraph via minimizing a quadratic smoothness term formed by a hypergraph Laplacian matrix subject to the known label constraints. This derive a natural probabilistic interpretation of this smoothness term. [10]

2.4 Intelligent Scissors

This is an interactive tool use for image segmentation. Intelligent scissors allow objects within digital images to be extracted quickly and accurately using simple gesture motions with a mouse. When the gestured mouse position comes in proximity to an object edge, a live-wire boundary "snaps" to, and wraps around the object of interest. Live-wire boundary detection formulates boundary detection as an optimal path search in a weighted graph. Optimal graph searching pro-vides mathematically piecewise optimal boundaries while greatly reducing sensitivity to local noise or other intervening structures. Robustness is further enhanced with on-the-fly training which causes the boundary to adhere to the specific type of edge currently being followed, rather than simply the strongest edge in the neighborhood. Boundary cooling automatically freezes unchanging segments and automates input of additional seed points. Cooling also allows the user to be much more free with the gesture path, thereby increasing the efficiency and finesse with which boundaries can be extracted. [12] [14]

2.5 Adaptive weighted distances

This present an interactive algorithm for soft segmentation of natural images. The user first roughly scribbles different regions of interest, and from them, the whole image is automatically segmented. This soft segmentation is obtained via fast, linear complexity computation of weighted distances to the user-provided scribbles. The adaptive weights are obtained from a series of Gabor filters, and are automatically computed according to the ability of each single filter to discriminate between the selected regions of interest. [13]

2.6 Hybrid Parallel Ant Colony Optimization (HPACO)

Hybrid Parallel Ant Colony Optimization (HPACO) is introduced in the field of Medical Image Processing. The suspicious region is segmented using algorithm HPACO. New CAD System is developed for verification and comparison of brain tumor detection algorithm. HPACO automatically determine the optimal threshold value of given image to select the initial cluster point then the clustering algorithm Fuzzy C Means automatically calculates the adaptive threshold for the brain tumor segmentation. [4]

2.7 Interactive Graph cut method based on improved Gabor features

In this, an interactive color image segmentation approach is proposed. The method integrates color features with reduced Gabor features and then employs graph cuts method to obtain the segmentations. The reduced Gabor features are extracted by principal component analysis (PCA) from Gabor features. This way can overcome the problem that high-dimension Gabor feature vectors may contain some features irrelevant to the discrimination of texture. Graph cuts methods manage to find optimal segmentation boundaries and regions by taking image segmentation as a minimum cut problem in a weighed graph. A globally optimal solution to the minimum cut problem can be computed with min-cut/max-flow algorithms. The original work was performed by Bolkov and Jolly [5], by means of optimizing an energy function based on Markov Random Field. Both region and boundary information were combined into a weighted graph. GrabCut is an iterated method to segmentation based on graph cuts. The combination of color information in the graph cuts method and an iterative learning approach increases its robustness. [15]

2.8 Interactive Segmentation Using Con-strained Laplacian Optimization

This present a novel interactive image segmentation approach with user scribbles using constrained Laplacian graph optimization. A novel energy framework is developed by adding the smoothing item in the cost function of Lapla-cian graph energy. This approach is the first to incorporate the normalized cuts and graph cuts algorithms into a unified energy optimization framework. [6]

2.9 Livewire

One of the representative methods is Livewire proposed by Flalcao et al. Livewire is a method, which determines the region contour by minimizing an objective function of the path connecting user-given points. With increasing, decreas-ing or modifying user-given points, the path is redetermined online. The objective function uses a similar-ity index between neighboring points, and the minimization can be done by means of a short path problem in graph theory. The method has been applied to various medical image analysis, for example, artery extraction from MRA images. The principal advantage of the meth-od is that it can ensure the segmentation accuracy and can be applied to any kind of images because the user evaluates the producing results based on their knowledge and the experience. However, because it evaluates only similarity index between neighboring points, it cannot evaluate the intensity distribution of the ROI. [2]

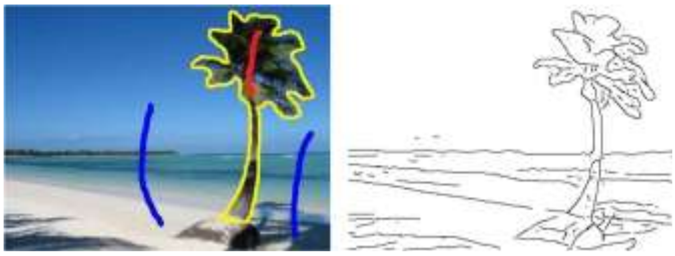

Fig. 1. (Left) Interactive image segmentation task with red and blue denoting seeds for the object and background. With the proposed framework, the whole palm tree can be cut out even when there is no seed at the trunk. (Right) Boundary map contains strong cues for segment labeling.We show how to fuse appearance and boundary information in segmentation. [7]

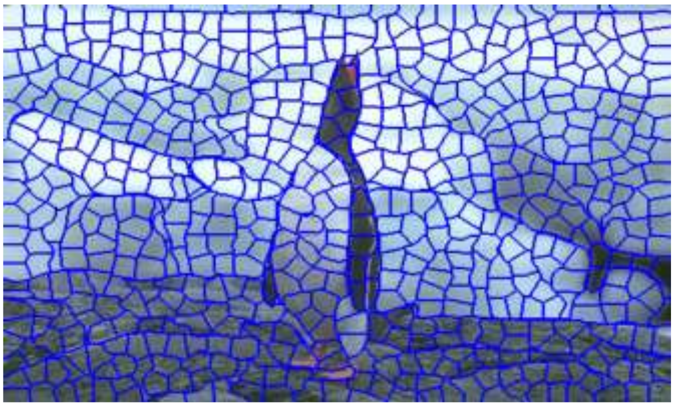

Fig. 2. Superpixels overlaid on the penguin image using the normalized-cut method as adopted by [16]. A small number of superpixels are shown for visualization purpose. [7]

3. Exterimental Results

To evaluate the performance of the proposed method, experiments were performed on different images. In this section we develop a system to examine the proposed algorithm and prove the accuracy and efficiency of our core algorithm.We got some experimental results by comparing the results of proposed method using ant clustering with the results of old method i. e. DPMVL without using ant clustering.The results are shown in Table1 and Table2. And also shown the output of both the methods in following figures.

Table 1: Experiments on proposed technique using ACO

Sr. No.	*Image*	*No. Of Cycles*	*Neighbourhood Gray Threshold*	*Time*	*Segmentation Remark*
1	bird1.bmp	10	10	13.0305	img1
2	bird1.bmp	3	5	15.7852	img2
3	bird1.bmp	3	8	15.0766	img3
4	bird1.bmp	3	10	14.0909	img4
5	bird1.bmp	3	16	16.0695	img5
6	bird1.bmp	5	5	14.2876	img6
7	bird1.bmp	5	10	15.3668	img7
8	bird1.bmp	5	15	15.0332	img8
9	flower.bmp	3	5	34.5583	flower1
10	flower.bmp	3	8	36.2582	flower2
11	flower.bmp	3	10	36.4696	flower3

12	flower.bmp	3	16	35.1834	flower4
13	flower.bmp	5	5	36.219	flower5
14	flower.bmp	5	10	35.3965	flower6
15	flower.bmp	5	15	35.5291	flower7
16	flower.bmp	10	10	35.9325	flower8
17	super_twodogs	3	5	42.8524	dog1
18	super_twodogs	3	8	37.1952	dog2
19	super_twodogs	3	10	36.9041	dog3
20	super_twodogs	3	16	39.6464	dog4
21	super_twodogs	5	5	38.3319	dog5
22	super_twodogs	5	10	37.41	dog6
23	super_twodogs	5	15	37.0872	dog7
24	super_twodogs	10	10	37.819	dog8

Table 1 shows the results after doing experiments in proposed technique which uses proposed methodology of ant clustering . We have done experiments on different images by giving inputs with two main parameters i.e. Number of cycles and Neighbourhood gray threshold. The segmentation is done by getting different results with time (seconds) by different input values of Number of cycle and Neighbourhood gray pixels. Program of the image features has two most sensitive parameters – T i.e. Threshold neighbourhood characteristics which determines key parameter cluster center and the second parameter is r which has put the default value r=300 which is the minimum distance for the cluster center owned. The program uses some basic parameters of ant swarm algorithm which has put some default values.They are a=2 i.e. pheromone index mainly represented by alpha , b=10 i.e. inspiration factor index mainly represented by beta , lamda=0.9 i.e. pheromone field values , rou=0.6 i.e. pheromone residual factor mainly represented by Rho , e=0.1 i.e. minimum spacing class. The segmentation result get as Ant clustering segmentation with segmented image from original image. Original image is of all types i.e. .gif, .jpg, .bmp, .png. The result also shows the ACO split with different parameters of ant swarm algorithm as r, T, itermax, e,a,b and rou. Here different effects has shown by changing the values of T and itermax i.e.Neighbourhood gray threshold and Number of cycle respectively. Time (seconds) is also calculated for performing segmentation process . Time differes for different parameters and for different images. The segmentation remark has the segmented image as an output with computed time. From number of experiments on one image by putting different combination of T and itermax values, one best output is selected with more sharper segmentation effect with less computed time. In Table 1 , we have done such different experiments on three different images and from them, the three best output is selected which is then used in Table 2 for comparison as shown below.

Table 2: Time Comparison between two techniques

Sr.No.	*Image*	*Time (technique without using ant clustering)*	*Time(with using ant clustering technique)*
1	bird1.bmp	18.0666	15.0766
2	flower.bmp	35.52	35.3965
3	super_twodogs.jpg	43.0778	37.1952

Table 2 shows the comparison between proposed technique which uses ant clustering and the old technique (DPMVL) without the concept of ant clustering. The best result with more sharper image segmentation with less time comsumption is taken from Table 1. This result is compared with the technique without using ant clustering. Here the time difference is showing that the proposed technique gets less time to complete the segmentation process with better result of segmentation than the technique without ant clustering.

Following are the results of image segmentation with using ant clustering in proposed technology and of old technology without using ant clustering. Fig 1, Fig 2 and Fig 3 are the best results come from Table 1 which are img3, flower6 and dog2 from the Segmentation remark column of Table 1. Fig 1. Shows the segmentation result of bird1.bmp image with time consumption 15.0766 seconds by giving inputs as Number of cycle=3 and Neighbourhood gray threshold=8. Fig 2. Shows the segmentation result of flower.bmp image with time consumption 35.3965 seconds by giving inputs as Number of cycle=5 and Neighbourhood gray threshold=10. Fig 3. Shows the segmentation result of super_twodogs.bmp image with time consumption 37.1952 seconds by giving inputs as Number of cycle=3 and Neighbourhood gray threshold=8.

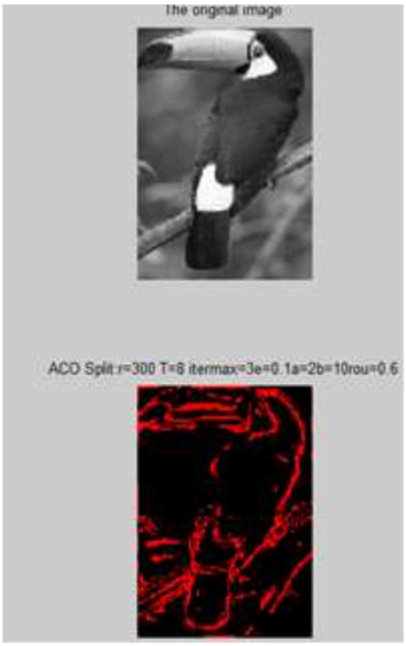

Fig 1. bird1.bmp with T=8 and itermax=3

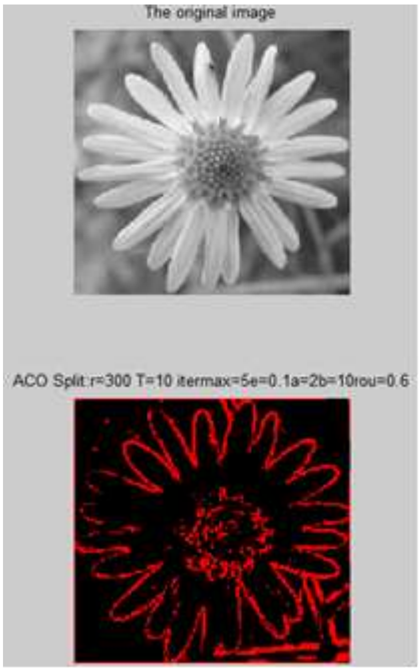

Fig 2. Flower.bmp with T=10 and itermax=5

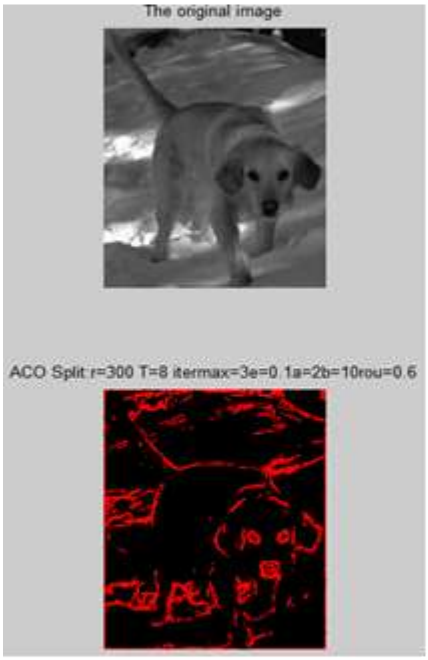

Fig 3. super_twodogs.bmp with T=8 and itermax=3

Following are the results of image segmentation in old technology without using ant clustering . Table 2. Shows the time comparison in which the time consumption for image segmentation process is more in old technology than the proposed technology .

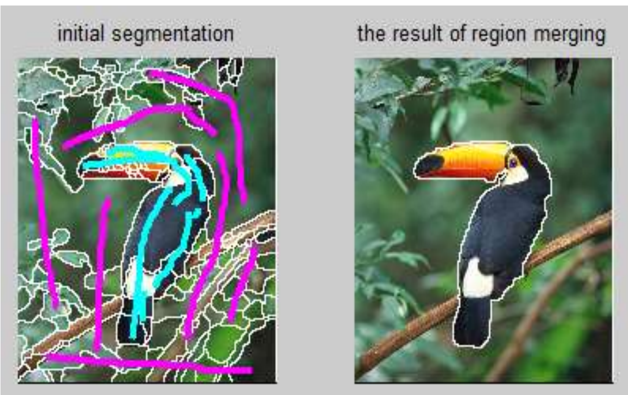

Fig 4. bird1.bmp

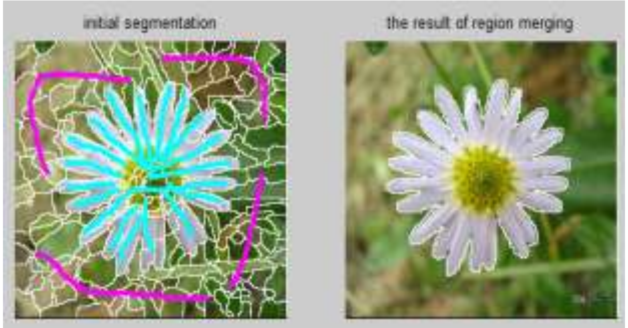

Fig 5. Flower.bmp

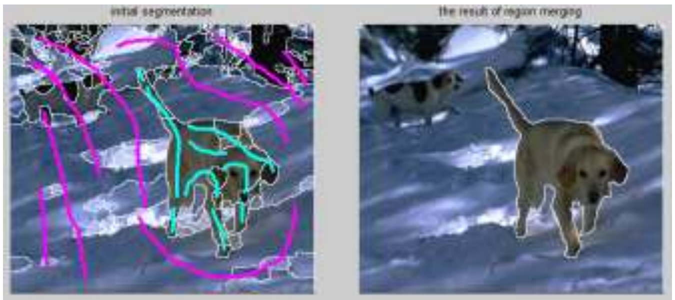

Fig 6. Super_twodogs.bmp

The process of segmentation of image is different in both the technologies here we have refered. In the proposed method, a rectangular region from the image is selected, the program of the selected area will be processed, thus reducing the running time of segmentation process. In DPMVL method, the object which is to be segmented and the background are marked differently with different colours by cursor and get the result of region merging.

4. Conclusion

In this paper, we have studied about Interactive image segmentation and various technologies used for it. From these technologies, in DPMVL, their approach draws strength from Dirichlet process-based nonlinear classification and the multiple views that include both color appearance and salient boundary information. As we have studied about Interactive image segmentation and its approaches, we got to know that the study of this topic is in depth and range of application areas will continue to increase. There are more possibilities of improvement in the effectiveness of segmentation process which can be fulfill in the proposed method by using combined MRF and Ant Colony Optimization. Proposed method can combines the advantages of different mentioned techniques, more algorithm extensibility, more interactivity and user control of segmentation process.We have compared between existing DPMVL technique and our proposed technique by doing severel experiments on different images. The numerical results showed that the proposed method gives the best performance.Further research can be focused on the simplification of the algorithm, which attempt to decrease the computation complexities within more less calculation time and misclassifications. Compared with the typical existing methods, the improved algorithm can achieve superior performance. In the future, we will do our best to reduce the complexity and computation time of the current work and extend it to the related research fields. Our approach can be extended in a variety of ways for future work.

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