Reboost Image Segmentation using Genetic Algorithm

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ABSTRACT

This paper present a Improved Algorithm for Image Segmentation System for a RGB colour image, and presents a proposed efficient colour image segmentation algorithm based on evolutionary approach i.e. improved Genetic algorithm. The proposed technique, without any predefined parameters determines the optimum number of clusters for colour images. The optimal number of clusters is obtained by using maximum fitness value of population selection. The advantage of this method lies in the fact that no prior knowledge related to number of clusters is required to segment the color image. Proposed algorithm strongly supports the better quality of segmentation. Experiments on standard images have given the satisfactory and comparable results with other techniques.

General Terms

Digital Image Processing, Algorithm, Image Segmentation, Genetic Algorithm.

Keywords

Color image segmentation, Genetic algorithm, Clustering.

1. INTRODUCTION

1.1 Image Segmentation

The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Some works have applied genetic algorithms (GA) to image processing [34] and to segmentation particularly [33, 32, 30, 31]. Indeed, GA is particularly efficient when the search space is really important and when the criterion to optimize is numerically complicated which is always the case in image processing. The main advantages of using GA for segmentation lie in their ability to determine the optimal number of regions of a segmentation result or to choose some features such as the size of the analysis window or some heuristic thresholds. In this paper we deal with various approaches for color image segmentation using GA along with many image segmentation techniques. We have tried to describe general segmentation techniques in this paper. In next section, we illustrate M-estimators algorithm (genetic algorithm), followed by comparison of various approaches led by researchers. Finally we end our work by giving the conclusion and perspectives.
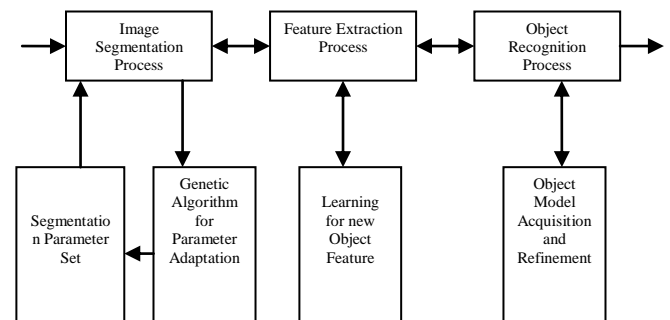

Fig.1: Flow Chart of Image Processing System

1.2 Genetic Algorithm

Genetic algorithms are based on natural selection discovered by Charles Darwin [40]. They employ natural selection of fittest individuals as optimization problem solver. Optimization is performed through natural exchange of genetic material between parents. Offspring's are formed from parent genes. Fitness of offspring's is evaluated. The fittest individuals are allowed to breed only. In computer world, genetic material is replaced by strings of bits and natural selection replaced by fitness function. Matting of parents is represented by cross-over and mutation operations.

A simple GA (Figure 1) consists of five steps [29]

1. Start with a randomly generated population of N chromosomes, where N is the size of population, l – length of chromosome x.

2. Calculate the fitness value of function $\varphi(x)$ of each chromosome x in the population.

3. Repeat until N offspring's are created:

a. Probabilistically select a pair of chromosomes from current population using value of fitness function.

b. Produce an offspring y_i using crossover and mutation operators, where $i = 1, 2, …, N$.

4. Replace current population with newly created one.
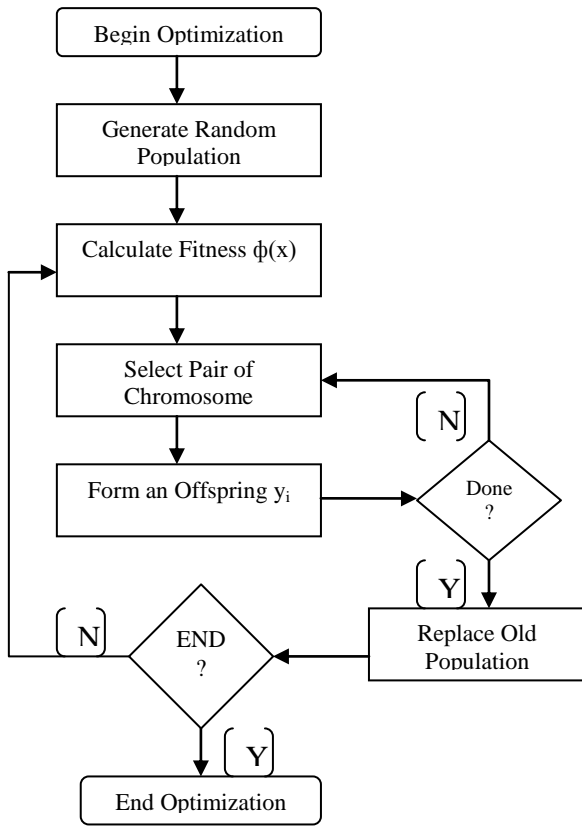
5. Go to step 2.

Fig.2: Flow Chart of Genetic Algorithm

2. LITERATURE REVIEW

Segmentation of a colour image composed of different kinds of texture regions can be a hard problem, namely to compute for an exact texture fields and a decision of the optimum number of segmentation areas in an image when it contains similar and/or unstationary texture fields. In this work, many researchers have proposed their algorithms for the same.

Vitorino Ramos, Fernando Muge [22] proposed an improvement of the k-means clustering algorithm. This algorithm uses minimum distance criteria as the fitness function. The minimisation is based on the different belonging combinations, of all points in the feature space. Naturally that, such task will be simply if the number of colours in one image to segment is low; however for high number of points in this 3D colour space (i.e., the different number of colours) this minimisation is hard to compute. The respective computer time for segmentation were 14.96, 12.76 and 37.02 minutes when string lengths were 124, 64 and 468 bits long.

ISODATA algorithm [28] proposed by Mohamad Awad, Kacem Chehdi, and Ahmad Nasri has some further refinements by splitting and merging of clusters. Clusters are merged if either the number of members (pixel) in a cluster is less than a certain threshold or if the centres of two clusters are closer than a certain threshold. Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value, and the number of members (pixels) is twice the threshold for the minimum number of members. 2) ISODATA is the only unsupervised classification method that is used with ERDAS IMAGINE.

P. Scheunders [37] proposed a genetic c-means algorithm which is an improvement to c-means clustering algorithm combining it with genetic algorithm. It is shown that this algorithm is less sensitive to the initial conditions than CMA. Furthermore GCMA is compared to several classical color image quantization algorithms, and its performance is shown to outperform the others, an effect which affects the visual image quality.

The GA-based GAHSI segmentation scheme [23] is a novel and simple approach to robustly segment an outdoor field image into plant and background regions under variable lighting conditions. The GAHSI obtained an equivalent segmentation performance to that obtained by applying cluster analysis to images acquired under specific lighting conditions. To further improve segmentation robustness, different imaging devices and color transformations as well as GA coding and operators need to be investigated in future research.

Li Zhuo et al [38] presented a mew GA based wrapper feature selection method GA-SVM for hyper-spectral data. The results showed that the GA-SVM method could significantly reduce the computation cost while improving the classification accuracy. The number of bands used for classification was reduced from 198 to 13, while the classification accuracy increased from 88.81% to 92.51%. The optimized values of the two SVM kernel parameters were 95.0297 and 0.2021, respectively, which were different from the default values as used in the ENVI software.

3. GENETIC ALGORITHM BASED CLUSTERING

The searching capability of GA's can be used for the purpose of appropriately clustering a set of unlabeled points in N-dimension into K clusters [1]. In our proposed scheme, the same idea can be applied on image data. We consider a colour image of size mxn and every pixel has Red, Green and Blue components. The basic steps of the GA-clustering algorithm for clustering image data are as follows:

3.1 Encoding

Each chromosome represents a solution which is a sequence of K cluster centres. For an N dimensional space, each cluster centre is mapped to N consecutive genes in the chromosome. For image datasets each gene is an integer representing an intensity value of the three components Red, Green and Blue.

3.2 Population initialization

Population is initialized in various rounds randomly and in each round the best chromosome survives for the next round processing.

3.3 Fitness computation

The fitness computation is accomplished in two steps. First, the pixel dataset is clustered according to the centres encoded in the chromosome under consideration, such that each intensity value $x_i(r,g,b)$ of colour image combined with three component red, green and blue (24 bit), i = 1, 2, ..., mxn is assigned to cluster with centre $z_j(r,g,b)$, j = 1, 2, ..., K,

If

$$\|xi(r,g,b) - zj(r,g,b)\| < \|xi(r,g,b) - zp(r,g,b)\|$$

$$p = 1,2,\ldots k \text{ and } p \neq j$$

The next step involves adjusting the values of the cluster centres encoded in the chromosome, replacing them by the mean points of the respective clusters. The new centre $Z_i(r,g,b)$ for the cluster C_i is given by

$$Zi(r,g,b) = \frac{1}{ni} \sum_{Xj \in Ci} Xj(r,g,b) , i = 1,2,...k$$

Now the fitness metric is computed by calculating the sum of intra cluster spread, i.e. finding the sum of Euclidean distance between the pixels and their respective cluster, given by

$$M = \sum_{i=1}^{k} Mi$$

$$M{\downarrow}i = \sum {\downarrow}\big(X{\downarrow}(j \in C{\downarrow}i)\big) :: \|X{\downarrow}j(r,g,b) - z{\downarrow}i(r,g,b)\|$$

The fitness evaluation of a chromosome is given by -

f = 1/M …..(1), thus our aim is to minimise the value of f.

3.4 Selection

Initially the fittest chromosome in every round of random population generation is moved to next generation, in the subsequent processing the fittest chromosome directly holds the 40% of the entire population and the rest of the population is hold by the chromosomes in the decreasing order of there fitness value.

3.5 Termination Criterion

We perform the population generation, fitness computation, crossover and selection for a predetermined number of generations, thus the algorithm is computed for the fixed number of generations and the best solution seen in the entire generation proceeds to final result.

Table 1. Analysis of Various Algorithms

	Population size	Selection	Crossover	Mutation	Fitness criteria	Stopping criteria	Coding	Characteristics	Future work
[22] Parallel Genetic Algorithm	100	Fitness proportional Model	One point crossover-Random selection of the point Crossover probability=0.5	Substitution of a randomly generate integer Mutation probability = 0.1	Distribution function	Threshold technique based on entropy of distributed function	Integer (Chromosome length =5)	Using a region based energy function, the active surface converges quickly	Automatic Initialization
[23] GAHSI Algorithm	48	Local tournament selection over roulette wheel method	Single point crossover Crossover probability=0.8	Insertion Mutation probability = 0.03	Weighted average function	Threshold technique based on UTOPIA parameter, if it failed for consecutive 5 times	Binary	Use of different imaging devices and color transformations	Adaptive adjustment of mutation rate
[24] Optimization Algorithm	6	Normalized geometric ranking selection method, Selection probability = 0.08	Arithmetic crossover, Crossover probability=0.6	Non uniform mutation, Mutation probability =0.05	Supervised evaluation function involving classification rate	Stability of standard deviation of the evaluation criterion	Based on genotype	Special focus on evaluation metrics	Implementation of priori knowledge

[25, 26] Hybrid Genetic Algorithm	31	Expected value plan and Elitist plan are two selection strategies	Unordered Subsequence Exchange Crossover (USXX) and Ordered Crossover, Crossover Probability=0.6	Remove and Reinsert, Mutation Probability=0.03	Linear Scaling function	Threshold Technique based on hybrid function	GA+SA+HGAPSA (Genetic Algorithm, Sequential Algorithm, Hybrid Genetic Algorithm with Parallel Simulated Annealing	Distributed environment with Remote Method Invocation concept	Removal of ambiguity in the population size. And more than two meta-heuristic algorithms may be interpreted to improve the solution space.
[27] Adaptive Genetic Algorithm	100	Proportional selection method	Crossover Probability, $0.5 < p_c < 1.0$	Mutation Probability, $0.001 < p_m < 0.05$	average fitness value f - maximum fitness value (fmax – f)	Sub-averaging the fitness value	Based on Schema Theorem i.e. Binary Coding	GA repeatedly converges to almost same fitness values	To resolve the problem of getting stuck in the local optimum when the population is scattered.
[28] ISODATA Algorithm	90	Roulette wheel method	Cluster centre replacement method Crossover probability = 0.6	Random substitution Mutation probability = 0.1	Objective Function	Stability of fitness values for 20 iterations	Bit level coding	Usage of multicomponent features	Parallel cooperation with more segmentation methods, such as FCM
[36] Dynamic GA based clustering (GADCIS)	30	Roulette Wheel selection	Single point crossover Crossover probability=0.9	Substitution Mutation probability =0.01	Cluster validity criteria based on Gaussian distribution	Fixed no. of iterations	Integer	No prior knowledge required	Work on generation of optimal no. of cluster centres
[37] Genetic c-means clustering (GCMA)	No. Of Clusters	Roulette wheel selection	One point crossover Crossover probability-=0.8	Insertion of single bit Mutation probability =0.05	Inverse of MSE	Stability of MSE	Binary or other	Develops a hybrid algorithm combining CMA and GA	Data clustering methods
[38] GA (based on SVM)	20	Stochastic uniform	Single point crossover Crossover probability=0.8 scattered	Scale=1.0 Shrink=1.0	Rank (fitness normalization)	Fixed no. of iterations	Binary	Classifies the given input data based on a set of training examples	Improvement in classification accuracy
[39] Elastic contour method	200	3 level contour function	One point crossover Crossover probability=0.6	Substitution Mutation probability =0.0001	Normalized histogram function	Fitness value ranging around 500-570	Integer	GA repeatedly converges to almost same fitness values	Deviation of no. of variants

4. PROPOSED WORK

The proposed new segmentation algorithm can produce a better result according to the segments created by optimal number of dynamic clusters. We consider a colour image f of size m x n. The proposed algorithm is:

1. Repeat step 2 to 4 till fixed no. of generations.

2. Randomly generate the cluster set using the randperm function.

3. Each pixel of the image is associated with the cluster number using min distance function which uses Euclidean formula as criteria.

4. We calculate fitness value of the chromosome by adding the distances of each pixel.

5. The chromosome with maximum fitness value is considered as the solution.

5. RESULT

Testing of proposed algorithm with standard color images, it has given satisfactory results, a tabular comparison between different clustering techniques are presented below. Column 2 of table gives the optimal range of clusters as proposed by [12]. Assumptions for segmenting the images are as follows: 20 rounds are processed for generating the initial population each generating random cluster from range 2 to 8 in RGB space, from each round cluster with maximum fitness value is passed to next generation and at each next iteration fitness value is being compared with fitness value of next cluster set. Each next generation contains the maximum fitness value, cluster set and also the cluster numbers. An iteration to 20 generations has been done to create the final results.
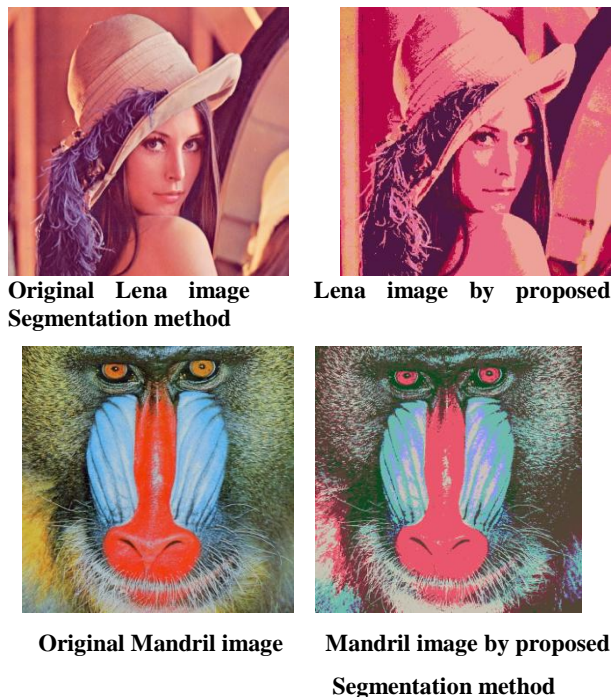

Original Lena image Segmentation method

Lena image by proposed

Original Mandril image

Mandril image by proposed

Segmentation method

Fig.3: Original Image and Segmented Image of Lena & Mandril

Table 2. Comparison of different Image Segmentation Algorithm

Image	Optimal range	Proposed method	DCPSO using v	SNOB
Mandril	5 to 10	5.32	6	39
Lena	5 to 10	4.47	6.85	31
Peppers	6 to 10	6.13	6.25	42
Jet	5 to 7	4.39	5.3	22

6. FUTURE WORK

The preceding sections provide an overview of the field of image segmentation, the review shows that many current algorithms are able to produce reasonable results on images of moderate complexity; several of these algorithms are efficient enough that they can be used as a pre-processing stage for higher level vision tasks such as recognition and tracking. The GAHSI algorithm [23] has its own characteristics; still it has scope of improvement in adaptive adjustment of mutation rate. Elastic contour method [39] can be improved by automatic deviation of no. of variants. In ISODATA algorithm [28], a parallel cooperation with various segmentation algorithms like FCM is required for further improvement. Still, there is some scope of improvement. Reviewing the existing algorithms, we conclude that absence of prior knowledge about the image's contents, it is in general not possible to determine how many regions are required for a reasonable segmentation. This problem manifests in two forms, Under-segmentation, which occurs when parts of the image that actually correspond to different objects, or to an object and the background, are assigned to the same region; and over-segmentation, which occurs when parts of the image corresponding to a single object are split apart.

7. CONCLUSION

Genetic Algorithm has many advantages in obtaining the optimized solution. It was proved to be the most powerful optimization technique in a large space. Genetic algorithm allows performing robust search for finding the global optimum. The result of the optimization depends on the chromosome encoding scheme and involvement of genetic operators as well as on the fitness function. However the quality of image segmentation can be improved by selecting the parameters in an optimized way. The desire for improvement after the GA reached a near optimal stage, led the authors to put some efforts on implementation of prior knowledge applications of GAs in clustering and grouping problems are intensively described in [29]. In the present approach, grey level intensities of RGB image channels are considered as feature vectors, and the k-mean clustering model (J.MacQueen, 1967) is then applied as a quantitative criterion (or GA objective fitness function), for guiding the evolutionary algorithm in his appropriate search.. In present scenario, various fast algorithms for speeding up the process of template matching are being implemented such as M-estimators for dealing with outliers. This fast algorithm ensures finding the global minimum of the robust template

matching problem in which a non-decreasing M-estimator serves as an error measure.

8. ACKNOWLEDGMENT

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