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Image Clustering using a Hybrid GA-FCM Algorithm

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ABSTRACT

Image analysis is a process of deriving object description from its image. It is of great theoretical and practical importance in the pattern recognition and image-based security systems domain. Image clustering is the partitioning of an image into the meaningful regions (image classes), based upon the properties of the pixel images, tone and texture. Image segmentation is an important technology for image processing. 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. Segmentation could be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up.

A number of clustering algorithms have been applied successfully to image clustering problems among which are K-means, Expectation-Maximization and Fuzzy C-means. This study considers the application of Fuzzy C-means for image clustering. However, the algorithm is sensitive to both noise and intensity heterogeneity since it does not take into account spatial contextual information. To overcome this limitation, GA is introduced to develop a new fuzzy segmentation technique which will optimize the performance of pure Fuzzy C-means. In light of this, a hybrid GA-FCM algorithm is developed to overcome this limitation and help obtain a more accurate clustering output.

Keywords: *Image Clustering, Image segmentation, Genetic algorithm, Fuzzy C-means.*

1. INTRODUCTION

There are many applications whether on synthesis of the objects or computer graphic images that require precise segmentation [14].

Multi-components images can be used to extract as much information as possible from an environment. In the last decade, multi-components images segmentation has received a great deal of attention for remote sensing and industrial applications because it significantly improves the discrimination and the recognition capabilities compared with gray-levels images segmentation methods [12]. Image clustering is the partitioning of an image into the meaningful regions (image classes), based upon the properties of the pixel images, tone and texture. Image analysis is a process of deriving object description from its image. It is of great theoretical and practical importance in the pattern recognition and image-based security systems domain. Image segmentation techniques can be classified into two [7]. One is a statistical approach which generates the probability distribution function of the pixel images or the parameters to characterize the properties of the tone and texture, and the other is a structural approach which analyzes the tone and texture in terms of their organization and relationship by the specified language [13].

Stochastic model-based image segmentation technique belongs to the statistical approach [6]. Some stochastic model-based image clustering techniques use tone descriptor and others use texture descriptor. In the tone clustering, the different image regions are modeled by region-dependent constant mean (average gray level) and variance (variation of gray level) and the distribution of different regions is modeled by different stochastic models, e.g., Markov random field, Gaussian random field etc. The clustering is then performed by maximum a posteriori or maximum likelihood estimation procedures, etc [5].

2. RELATED WORK

Various works have applied genetic algorithms (GA) to image processing and to segmentation particularly. As segmentation can be seen as a process which finds out the optimal regions partition of an image according to a criterion, GA are well adapted to achieve this goal. Indeed, GA are 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. The GA proposed by Holland (1975) are a general-purpose global optimization technique based on randomized search. They incorporate some aspects of iterative algorithm. A genetic algorithm is based on the idea that natural evolution is a search process that optimizes the structures it generates. An interesting characteristic of GA is their high efficiency for difficult search problems without being stuck in local extremum. In a GA, a population of individuals, described by some chromosomes, is iteratively updated by applying operators of selection, mutation and crossover to solve the problem. Each individual is evaluated by a fitness function that controls the population evolution in order to optimize it.

[13] used GA to optimize the parameters of a segmentation method under various conditions of image acquisition. Another illustration of the interest of GA for image segmentation is given by [14]. They combined GA and Kohonen's self-organizing map for the clustering of textured images. The fuzzy C-means algorithm was used to generate a fine segmentation result. [9] proposed a genetic algorithm dedicated to texture images where the fitness function is based on texture features similarity. [12] use genetic algorithms to combine different segmentation results obtained by different agents. A recent work proposed by [7] uses a fitness function that can be considered as an evaluation criterion in a hierarchical process. None study of the used fitness function has been done in order to quantify its reliability.

The most important components of the proposed methods concern both the modelling of the problem with GA and the definition of the fitness function. GA can be used to find out the optimal label of each pixel, to determine the optimal parameters of a segmentation method (number of regions for example), or to merge regions of a fine segmentation result. Concerning the fitness function, it can be an unsupervised quantitative measure of a segmentation result or a supervised one using some a priori knowledge.

Genetic algorithms determine the optimal value of a criterion by simulating the evolution of a population until survival of best fitted individuals. The survivors are individuals obtained by crossing-over, mutation and selection of individuals from the previous generation. We think that GA is a good candidate to find out the optimal combination of segmentation results for two main reasons. The first one is due to the fact an evaluation criterion is not very easy to differentiate. GA is an optimization method that does not necessitate to differentiate the fitness function but only to evaluate it. Second, if the population is enough important considering the size of the search space, we have good guarantees that we will reach the optimal value of the fitness.

Individual mutation: individual's genes are modified in order to be better adapted to the environment. An approach is the non-uniform mutation process which randomly selects one chromosome x_i, and sets it as equal to a non-uniform random number.

The genetic algorithms distinguish themselves in the field of methods of optimization and search for the assimilation of the Darwinian paradigm of the evolution of species.

The fuzzy *c*-means (FCM) clustering algorithm was first introduced by Dunn, (1974) and later was extended by Bezdek, (1981). The algorithm is an iterative clustering method that produces an optimal *c* partition by minimizing the weighted within group sum of squared error objective function.

The most widely used method for segmentation of textured image clustering is the Fuzzy C-Means (FCM) algorithm, which is a "fuzzy relative" to the simple c-means technique. The fuzzy c-means clustering algorithm has been utilized in a wide variety of image processing applications such as medical imaging and remote sensing. It performs a fuzzy partition of a given data set. The advantages of this method are its straightforward implementation, its fairly robust behavior, its applicability to multichannel data and the ability of uncertainty data modeling.

Fuzzy C-means is a clustering method which allows a piece of data to belong to two or more clusters, which is frequently used in computer vision, pattern recognition and image processing [8], [20], [1]. The FCM algorithm obtains segmentation results by fuzzy classification [21]. Unlike hard classification methods which group a pixel to belong exclusively to one class, FCM allows a pixel to belong to multiple classes with varying degree of memberships, [6]. FCM approach is quite effective for image segmentation.

The fuzzy C-means algorithm (FCM) has been utilized in a wide variety of image processing applications such as medical imaging [6], [22] and remote sensing [15], [11]. The algorithm and various modifications of it with focus on practical applications in both industry and science are discussed. Its advantages include a straightforward implementation, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data. FCM is more effective to the fuzzy boundary region segment, but the biggest disadvantage is that no better way to determine the C value of clustering and the initial cluster centers, essentially, FCM is a local search optimization algorithm, it will converge to the local minimum point and this clustering effect would have a greater impact if the initial selection value are not properly [10], [16].

[17] proposed a fuzzy rule-based scheme called the rule-based neighborhood enhancement system to impose spatial continuity by post-processing the clustering results obtained using FCM algorithm. In their another approach

, a spatial constraint is imposed in fuzzy clustering by either adding or subtracting a small positive constant to the centre pixel in a 3×3 window, depending on whether the most possible cluster assigned for the pixel in the 8-neighborhood is the same as or different to that of the centre pixel. [19] proposed a geometrically guided FCM (GG-FCM) algorithm based on a semi-supervised FCM technique for multivariate image segmentation. In their work, the geometrical condition information of each pixel is determined by taking into account the local neighborhood of each pixel.

Recently, some approaches were proposed by [18] and [23] for increasing the robustness of FCM to noise by directly modifying the objective function. [18] introduced a regularization term into the standard FCM to impose neighborhood effect. Later, [23] incorporated this regularization term into a kernel-based fuzz clustering algorithm. Although the above two methods are claimed to be robust to noise, they are confronted with the problem of selecting the parameters that control the role of the spatial constraints. In addition, they are computationally complex.

3. MATERIALS AND METHODS

3.1 Problem Statement

Accurate and robust image clustering was identified as one of the most challenging issues facing the pattern recognition domain. This difficulty is compounded by the low spatial resolution and high noise characteristics of these images. Image clustering is the partitioning of an image into the meaningful regions (image classes), based upon the properties of the pixel images, tone and texture.

Various image segmentation techniques can be classified into two major approaches:

1) a statistical approach which generates the probability distribution function of the pixel images or the parameters to characterize the properties of the tone and texture, and

2) a structural approach which analyzes the tone a texture in terms of their organization and relationship by the specified language. Stochastic model-based image segmentation technique belongs to the statistical approach.

The fuzzy C-means (FCM) clustering algorithm was largely used in various image segmentation approaches. However, the algorithm is sensitive to both noise and intensity heterogeneity since it does not take into account spatial contextual information. As a result, there is an increasing need for optimizing the classification accuracy of FCM. To overcome this limitation, a new fuzzy segmentation technique is required.
However, GA is a meta-heuristic optimization technique that imitates the long-term optimization process of biological evolution for solving mathematical optimization problems. They are based upon Darwin's principle of the 'survival of the fittest'. Problem solutions are abstract 'individuals' in a population. Each solution is evaluated by a fitness function. The fitness value expresses survivability of a solution, i.e. the probability of being a member of the next population and generating 'children' with similar characteristics by handing down genetic information via evolutionary mechanisms like reproduction, variation and selection, respectively. Reproduction and variation is achieved by mutation of genes and crossover.

The latter combines characteristics of two solutions for deriving two new solutions. The coding of the problem into a genetic representation, e.g. the sequence of the phenotype's parameters on a genotype, is crucial to the performance of GA. Moreover, the fitness function has great impact on performance [2].

In the light of the above, this study is required to develop a hybrid GA-FCM algorithm which is expected to overcome this limitation and help obtain a more accurate clustering output.

3.2 Fuzzy C-Means Algorithm

Fuzzy C-Means Algorithm (FCM) is the most popular objective function based fuzzy clustering algorithm, the objective function used in FCM is given by Equation (1)

$$J_{FCM}^{m}(U, A, X) = \sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m} d_{ij}^{2} = \sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m}\left\|\underline{x}_j - \underline{a}_i\right\|^2 \quad (1)$$

$\mu_{ij} \in [0,1]$ is the membership degree of data object $\underline{x}_j$ in cluster C_i and it satisfies the following constraint given by Equation (2)

$$\sum_{i=1}^{c}\mu_{ij} = 1,\ \forall j = 1,2,\ldots,n \qquad (2)$$

C is the number of clusters, m is the fuzzy index, m>, which controls the fuzziness of the method. They are both parameters and need to be specified before running the algorithm. $d_{ij}^{2} = \left\|\underline{x}_j - \underline{a}_i\right\|^2$ is the square Euclidean distance between data object $x\ j$ to center $a\ i$.

Minimizing objective function Equation (1) with constraint Equation (2) is a non-trivial constraint nonlinear optimization problem with continuous parameters ai and uij, Hence there is no obvious analytical solution. Alternatively optimizing one set of parameters while the other set of parameters are considered as fixed, is used here. The updating function for *i*, *a* and *j x* is obtained as Equation (3) and (4).

3.3 Optimization Method: Genetic Algorithm

Genetic algorithms determine the optimal value of a criterion by simulating the evolution of a population until survival of best fitted individuals. The survivors are individuals obtained by crossing-over, mutation and selection of individuals from the previous generation. GA is a good candidate to find out the optimal combination of segmentation results for two main reasons.

The first one is due to the fact an evaluation criterion is not very easy to differentiate. GA is an optimization method that does not necessitate to differentiate the fitness function but only to evaluate it.

Second, if the population is enough important considering the size of the search space, there exists good guarantees that the optimal value of the fitness will be reached.

There are three major design decisions to consider when implementing a GA to solve a particular problem. A representation for candidate solutions must be chosen and encoded on the GA chromosome, fitness function must be specified to evaluate the quality of each candidate solution, and finally the GA run parameters must be specified, including which genetic operators to use, such as crossover, mutation, selection, and their possibilities of occurrence. A genetic algorithm is defined by considering four essential data:

1. *genotype*: the segmentation result of an image I is considered as an individual described by the class of each pixel,

2. *initial population*: a set of individuals characterized by their genotypes. It is composed of the segmentation results to combine,

3. *fitness function*: this function enables us to quantify the fitness of an individual to the environment by considering its genotype. The evaluation criteria described in the previous sections can be used as a fitness function in the unsupervised case or in and in the semi-supervised cases,

4. *operators on genotypes*: they define alterations on genotypes in order to make the population evolve during generations. Three types of operators are used; selection, mutation and crossover.

3.3.1 Individual Mutation

Individual's genes are modified in order to be better adapted to the environment. Mutation is the genetic operator responsible for maintaining diversity in the population. Mutation operates by randomly "*flipping*" bits of the chromosome, based on some probability. A usual mutation probability is 1/p, where p is the length of each of the two parts of the chromosomes. This probability should usually be set fairly low. If it is set to high, the search will turn into a primitive random search.

We use the non-uniform mutation process which randomly selects one chromosome xi, and sets it as equal to a non-uniform random number:

$$x_i' = \begin{cases} x_i + (b_i - x_i) f(G) & if\ r_1 < 0.5 \\ x_i - (x_i + a_i) f(G) & if\ r_1 \geq 0.5 \end{cases} \quad (6)$$

Where

$f(G) = (r_2(1 - \frac{G}{G_{max}}))^b$

$r_1, r_2 : numbers\ in\ the\ interval\ [0,1]$

$a_i, b_i : lower\ and\ upper\ bound\ of\ chromosome\ x_i$

$G : the\ current\ generation$

$G_{max} : the\ maximum\ number\ of\ generations$

$b : a\ shape\ parameter$

3.3.2 Selection of an Individual

Individuals that are not adapted to the environment do not survive to the next generation. We used the normalized geometric ranking selection method which defines a probability P_i for each individual i to be selected as following:

$$P_i = \frac{q(1-q)^{r-1}}{1-(1-q)^n} \quad (7)$$

Where

$q : the\ probability\ of\ selecting\ the\ best\ individual$

$r : the\ rank\ of\ individual,\ where\ 1\ is\ the\ best$

$n : the\ size\ of\ the\ population$

3.3.3 Crossing-Over

Crossover, the critical genetic operator that allows new solution regions in the search space to be explored, is a random mechanism for exchanging genes between two chromosomes using the one point crossover, two point crossover, or homologue crossover. Offspring replaces the old population using the elitism or diversity replacement strategy and forms a new population in the next generation. Two individuals can reproduce by combining their genes. We use the arithmetic crossover which produces two complementary linear combinations of the parents:

$$X' = aX + (1-a)Y$$

$$Y' = (1-a)X + aY \quad (8)$$

where

X, Y: genotype of parents
a: a number in the interval [0, 1]
X', Y': genotype of the linear combinations of the parents

3.3.4 Stopping Criterion

This criterion allows to stop the evolution of the population. We can consider the stability of the standard deviation of the evaluation criterion of the population or set a maximal number of iterations (we used the second one with the number of iterations equals to 1000).

Given these information, the execution of the genetic algorithm is carried in the following steps:

1. Definition of the initial population (segmentation results) and computation of the fitness function (evaluation criterion) of each individual,
2. Mutation and crossing-over of individuals,

3. Selection of individuals,

4. Evaluation of individuals in the population,

5. Back to step 2 if the stopping criterion is not satisfied.

3.3.5 Fitness Function

The main goal of feature selection is to use fewer features to obtain the same or better performance. Fitness function is developed to evaluate the effectiveness of each individual in a population, so it has an individual as an input and it returns a numerical evaluation that must represent the goodness of the feature subset. The search strategy's goal is to find a feature subset maximizing this function. Fitness = FCM_accuracy

3.4 GA Parameters

GA approach was used to select a set of good finite feature selection for FCM. The parameters with their corresponding default value are presented in Table 1 below.

Table 1: Parameters set used for the genetic process

Parameter	Default Value	Signification
Population size	100	Number of Chromosomes created in each generation
Crossover rate	0.8	Probability of crossover
Mutation rate	0.1	Probability of mutation
Number of generations	500	Maximum number of generations

The Proposed GA-FCM model for segmentation of image is shown in the figure below:

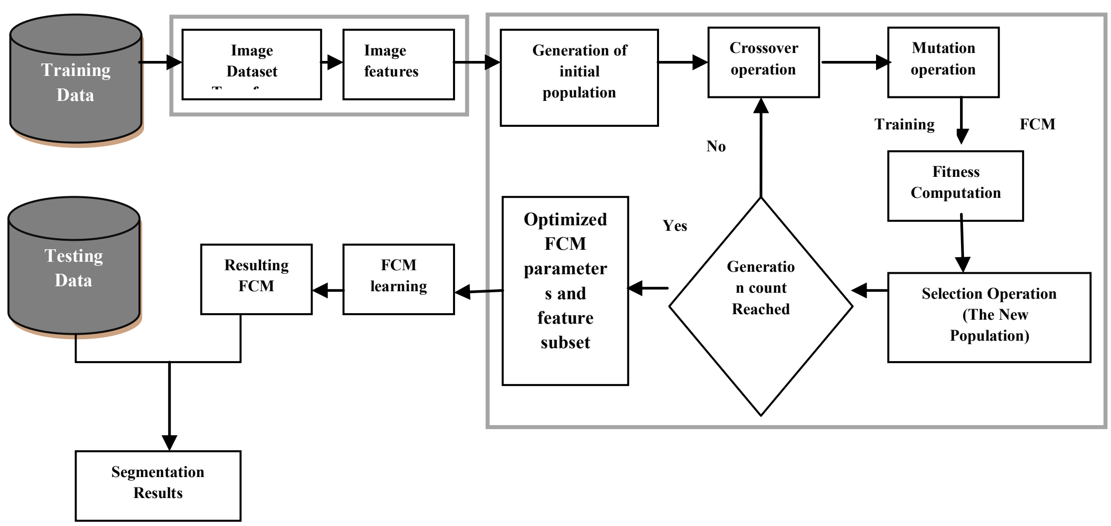

Figure 1: Proposed GA-FCM Model

3.5 Performance Evaluation Metrics

The performance evaluation metrics considered in this study are;

Simulation time: This is total finite time in seconds for a program to compile, run and display results after being loaded.

Accuracy: Accuracy (A) is the percentage of all image that are correctly segmented.

Space complexity: it is the total amount of memory space used in the course of the computation.

3.6 Simulation Tool

The programming tool used to implement the algorithms is MATLAB. This is because MATLAB is a very powerful computing system for handling the calculations involved in scientific and engineering problems. MATLAB stands for MATrix LABoratory. With MATLAB, computational and graphical tools to solve relatively complex science and engineering problems can be designed, developed and implemented. Specifically, MATLAB 2007b was used for the development.

4. RESULTS AND DISCUSSION

The GA-FCM image segmentation method is proposed. By introducing genetic algorithm, a threshold based on the pixel value of the hue, saturation and intensity (H, S, I) separately is set, these color information of the object can represent the parts with the image close to these color information. The character of HSI is used to analyze color because they are the three components of the original color. Since the hue, saturation and intensity are independent of one another, they were used to process the image separately without worrying about their associated correlations. On the other hand, if the character of RGB has been used instead, the color of the segmented results would have changed correspondingly when a few pixel values are changed. Afterwards, to compensate the lack of the boundary when segmenting the image by the character of HSI, FCM is used to extract the boundaries of the target image. Matlab was used to implement the edge function in FCM to extract the approximate boundaries. After getting the approximate boundaries, the information of the pixels which reside in the extracted boundaries was obtained.

Finally, final modification was performed to remove any noise that may have been introduced by the inclusion of GA. To eliminate the noise, the disconnect boundaries was connected by performing dilation on the boundaries of the target image, and then the combined image was connected with the dilated boundaries to eliminate the trivial noise that doesn't reside in the target image. The result of the intersection is the final image.

4.1 Performance Comparison

Table 2: Performance of FCM and Hybrid GA-FCM algorithm on image clustering

ALGORITHM	SIMULATION TIME (SEC)	ACCURACY	SPACE COMPLEXITY	OBJECTIVE FUNCTION	ITERATION
FCM	2.6364	100%	21284K	7.026723	25
GA_FCM	1.1232	100%	2868K	0.000000	0

Table 2 shows the various performance metrics used to evaluate the performance of FCM and the hybrid algorithm developed (GA-FCM) for image clustering. In this study, GA was used to optimize the time and space requirement of FCM image clustering algorithm while keeping segmentation accuracy at bay; this accounted for why the accuracy is the same. The table summarizes the results obtained based on the performance metrics for both algorithms including the Simulation time, Space complexity, objective function optimization and the number of iterations generated. The hybrid GA-FCM has a better performance over the FCM image clustering algorithm based on these metrics as summarized in the above table.

4.2 Description of GA-FCM Segmentation Implementation

The figure below shows the FCM segmentation with 25 iteration and a total objective function of 7.026723. The clustering used 2.6364s for simulation.

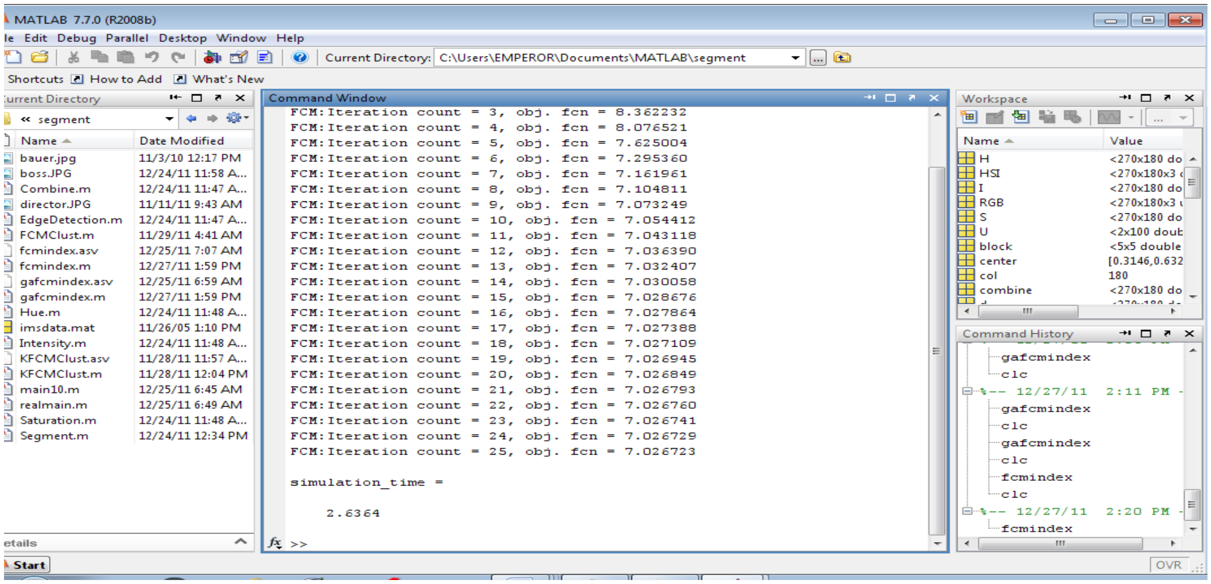

Fig 2: Showing the Result of the Image Clustering Using FCM Clustering Algorithm

INITIAL IMAGE **SEGMENTED IMAGE USING FCM**

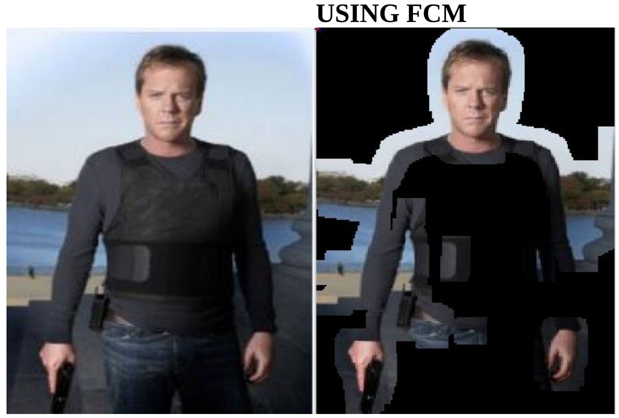

Figure 3: Showing the initial and the segmented image using FCM clustering algorithm

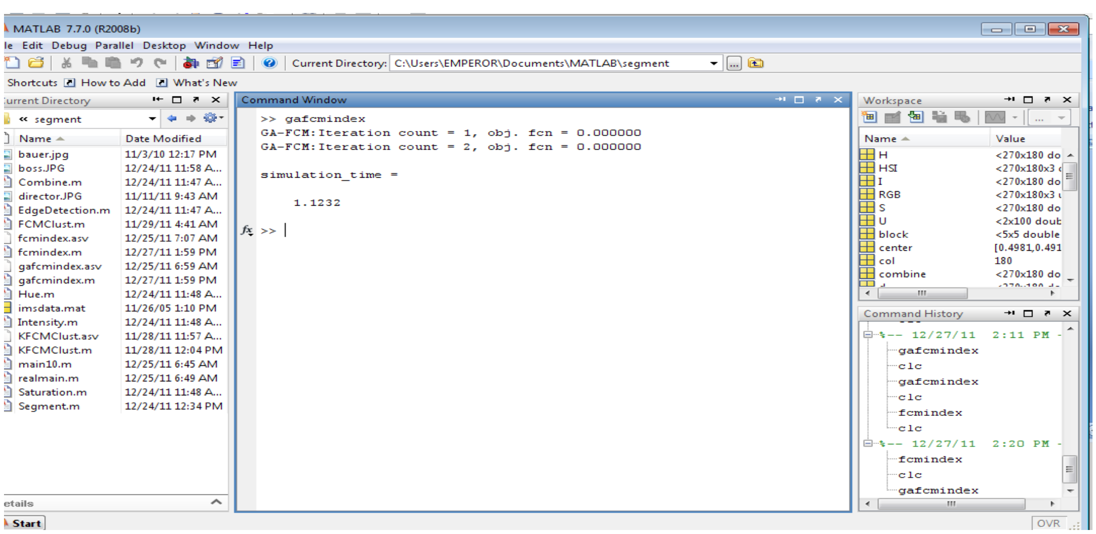

Figure 4: Showing the result of the Image Clustering using Hybrid GA-FCM clustering algorithm

The figure above shows the Hybrid GA_FCM clustering with 2 iterations and 0.000000 objective function.

Figure 5: Showing the initial and the segmented image using FCM clustering algorithm

5. CONCLUSION

FCM image clustering has been observed to consume a lot of computational resources, has more simulation time and involves a lot of iteration which makes it more expensive to use for image segmentation. To eliminate these drawbacks, A GA approach is adopted to select features that are most favorable to FCM clustering, which is named as GA-FCM. This reduced the number of support vectors clustered using FCM. A fitness function was introduced in GA to help eliminate irrelevant features whose fitness value falls below the set fitness parameter. The simulation results on image clustering showed that comparing with original FCM clustering algorithm, the number of support vector decreases while better clustering results were obtained using GA-FCM.

The result above indicates that Hybrid GA_FCM image clustering has a remarkable improvement on the simulation time and space requirement over FCM in the face of image segmentation showing that GA_FCM has eliminated the drawbacks of FCM.

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