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Image Segmentation through Clustering Based on Natural Computing Techniques

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1. Introduction

Natural Computing (NC) is a novel approach to solve real life problems inspired in the life itself. A diversity of algorithms had been proposed such as evolutionary techniques, Genetic Algorithms and Particle Swarm Optimization (PSO). These approaches, together with fuzzy and neural networks, give powerful tools for researchers in a diversity of problems of optimization, classification, data analysis and clustering.
Clustering methods are usually stated as methods for finding the hidden structure of data. A partition of a set of N patterns in a p-dimensional feature space must be found in a way that those patterns in a given cluster are more similar to each other than the rest. Applications to clustering algorithms range from engineering to biology (Xu & Wunsch II, 2005; Xu & Wunsch, 2008; Jain et al., 1999).
Image segmentation techniques are based on Pattern Recognition concepts and such a task aims to identify behavior in a data set. In the context of image segmentation, the data set represents image data, coded as follows: the light intensity value (the pixel data) represents a pattern, an item in the data set, and the color information is represented by columns (the feature vectors). Clustering techniques represent the non-supervised pattern classification in groups (Jain et al., 1999). Considering the image context, the clusters correspond to some semantic meaning in the image, which is, objects. More than simple image characteristics, these grouped semantic regions represent information; and image segmentation is applicable in an endless list of areas and applications, for example: computer-aided diagnosis (CAD) being used in the detection of breast cancer on mammograms (Doi, 2007), outdoor object recognition, robot vision, content-based image, and marketplace decision support.
Among the many methods for data analysis through clustering and unsupervised image segmentation is: Nearest Neighbor Clustering, Fuzzy Clustering, and Artificial Neural Networks for Clustering (Jain et al., 1999). Such bio and social-inspired methods try to solve the related problems using knowledge found in the way nature solves problems. Social inspired approaches intend to solve problems considering that an initial and previously defined weak solution can lead the whole population to find a better or a best so far solution.
This chapter presents concepts and experimental results of approaches to data clustering and image segmentation using (NC) approaches. The main focus are on Evolutionary Computing, which is based on the concepts of the evolutionary biology and individual-to-population adaptation, and Swarm Intelligence, which is inspired in the behavior of individuals, together, try to achieve better results for a complex optimization problem.

Genetic and PSO based K-means and fuzzy K-means algorithms are described. Results are shown for data clustering using UCI datasets such as Ruspini, Iris and Wine and for image texture and intensity segmentation using images from BrainWeb system.
The remainder of the chapter is organized in the following form: section 2 describes Data Clustering and Image Segmentation; section 3 presents the state-of-the-art in Image Segmentation techniques; section 4 presents Natural Computing; section 5 focuses on clustering using Natural Computing methods. Section 6 presents experimental results and discussion and section 8 gives the conclusions and final considerations.

2. Image segmentation and data clustering

Digital Image Processing is an extremely important and fundamental task to image analysis, whose main task is the separation or isolation of image regions, reducing the data space to be analyzed. On monochromatic images, image segmentation algorithms are based on the following image gray level properties (Gonzalez & Woods, 2003):
a. **Discontinuity**: the objective is to find hard changes on gray level, using this information as the method to edge detection; and
b. **Similarity**: closest pixels are very similar.
Some of the main challenges to the scientific community are related to the development of techniques that realize the automatic or unsupervised image segmentation. In controlled environment the image segmentation process is easily achieved than in a non-controlled environment, where light and other circumstances affect physical process of image acquisition.
Image segmentation applications contemplate many areas of Computer Graphics. In the case of Computer Vision, one of the objectives is make robots move in a semi or non-controlled environment, and realize tasks like find and interact with specific objects. Another area of interest is the automatic vehicle guiding. On Image Understanding and Analysis there is Content Based Image Retrieval, that aims to develop efficient search engines that can find items on an image database by using a reference image, detecting similarities.
The mathematical formulation of segmentation is defined as follows (Raut et al., 2009):
Let I be the set of all image pixels, then by applying segmentation we obtain different unique non-overlapping regions $\{S_1, S_2, S_3, ..., S_n\}$ which, when combined, form I:

$$\bigcup_{i=1,n}^{n} S_i = I \quad \text{where } S_i \cap S_j = \varnothing \tag{1}$$

where:
a. S_i is a connected region, i = 1, 2, …, n
b. $P(S_i)$ = TRUE for i = 1, 2, …, n
c. $P(S_i \cup S_j)$=FALSE for $i \neq j$
d. $P(S_i)$ is a logical predicate defined over points in set S_i.
Eq. 1 is a condition that indicates that segmentation must be complete: every pixel in the image must be covered by segmented regions, which must by disjoint.

2.1 Data clustering

In a very simple level of abstraction, the image segmentation process is very close to the clustering problem. To find clusters in a data set is to find relations amongst unlabeled data. The "relation" means that some data are in some way next to another that they can be grouped. It is found in (Jain et al., 1999) that the components of a clustering task are:

1. **Pattern representation includes**: feature selection, which identifies the most effective subset of the original features to use in clustering; and feature extraction, which is the preprocessing of the input features.
2. A **Distance measure** is used to determine pattern proximity. A simple, and, perhaps, the most used, distance function is the Euclidean Distance.
3. **Clustering** relates to finding the groups (or, labeling the data) and it can be hard (an element belongs to one group only) or fuzzy (an element belongs to one group following a degree of membership).
4. **Data abstraction** is an optional phase and extracts a simple and compact representation of a data set and, in the case of data clustering, some very representative patterns are chosen: the centroids.
5. **Assessment of output** is the process of evaluating the clustering result. Cluster validation techniques are, also, a traditional approach to dynamic clustering (Omram et al., 2006).

Two classical clustering algorithms are used in this work: K-means (Forgy, 1965) and Fuzzy C-Means (Zadeh, 1994).

2.1.1 K-means

K-means objective if minimize the *J* function, which represents the minimization of the distance between objects (patterns) and clusters:

$$J_{\text{K-means}} = \sum_{k=1}^{K} \sum_{j \in S_k} d^2(x_j, c_k) \tag{2}$$

where:

a. k is the number of clusters evaluated (in a space defined by S_k)
b. x_j is the pattern j evaluated in relation to the centroid c_k
c. $d^2(x_j, c_k)$ is the distance between pattern x_j and centroid c_k

The algorithm performs as follows:

a. Initialize K centroids (for example, randomly)
b. Until a stop criterion is not satisfied
   a. Calculate the distances between all elements in the dataset and the K centroids. Elements closer to centroids form clusters
   b. Centroids are updated (assume the clusters values)

The main advantages of this algorithm are (Turi, 2001):

a. Is easy to implement
b. The complexity is $O(N_p)$, which makes it very applicable to large datasets.

The main disadvantages are (Davies, 1997):

a. It is dependent on the dataset
b. It is a greedy algorithm, which depends upon initial conditions that can lead to sub-optimal solutions
c. The number of clusters (K) must be informed by the user.

2.1.2 Fuzzy C-means

The Fuzzy C-means (FCM) algorithm is defined by (Bezdek et al., 1987) as follows: let $c \geq 2$ be an integer; let $X = \{x_1,...,x_n\}$ be a finite dataset which contains at least $c < n$ distinct points; and let R^{cn} be the set of all real matrices $c \times n$. A partition of the X set is represented by a matrix $U = [u_{ik}] \in R^{cn}$ whose elements satisfy the following equations:

$$u_{ik} \in [0,1], \quad 1 \leq i \leq c; 1 \leq k \leq n \tag{3}$$

$$\sum_{i=1}^{c} u_{ik} = 1, \quad 1 \leq k \leq n \tag{4}$$

$$\sum_{k=1}^{n} u_{ik} > 0, \quad 1 \leq i \leq c \tag{5}$$

where v_i is the centroid of cluster i (most representative element). Partitions and centroids are chosen from the minimization of the functional J:

$$J_{\mathrm{m}}(U,v) = \sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^m |x_k - v_i|^2 \tag{6}$$

where $1 \leq m' < \infty$ is the *fuzzyficator parameter* and $|.|$ is a distance measure. Yet, the following condition is necessary for every i:

$$v_i = \frac{\sum_{i=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m} \tag{7}$$

and, for every k, in such a way that if $d_{ik} = |x_k - v_i|^2 > 0$ for every i, then the following is true for every i:

$$u_{ik} = \frac{1}{\sum_{i=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{1}{m-1}}} \tag{8}$$

This chapter understands Clustering and Image Segmentation as a similar task. We make no distinction between them, in the view of the experiments. For a review on clustering techniques, please refer to (Jain et al., 1999; Xu & Wunsch, 2005; Hruschka et al., 2009).

3. The state-of-the-art

Some image segmentation techniques are presented by (Raut et al., 2009) and they can be classified in:

a. **Threshold-based techniques**: are generally used for gray level images. A threshold value T is defined to split the image in two parts: foreground and background based on pixel value

b. **Histogram-based techniques**: the histogram of all the pixels is calculated, and according to peaks and valleys different clusters are formed
c. **Edge detection techniques**: first and second order derivatives are used for detection of edges. Edges are divided in two categories: intensity edges and texture edges
d. **Region-based techniques**: uses region growing and region splitting-merging procedures. Region growing procedure groups pixels or sub regions into large regions based on predefined criteria. Region split-merge divides image into disjoint regions and then either merge and/or split to satisfy prerequisite constraints
e. **Watershed Transformation techniques**: considered to be more stable than the previous techniques, it considers the gradient magnitude of an image (GMI) as a topographic surface. Pixels having the highest GMI correspond to watershed lines, which represent region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minima (LMI). Pixels draining to a common minimum form a catchments basin, which represent the regions.

Clustering can be formally considered as a particular kind of NP-hard grouping problem (Hruschka et al., 2009). This assumption has stimulated much research and use of efficient approximation algorithms.

Many variations of approaches have been introduced over last 30 years, and image segmentation remains an open-solution problem. Recently there has been an increase in the presence of optimization-based techniques. (Angus, 2007) proposed a technique for a Population-based Ant Colony Optimization (PACO) to Multi-objective Function Optimization (MOFO). (Raut et al., 2009) proposed an approach used for prediction using segmentation. They use a Graph-Partitioning technique which has some bases on Ontology. In summary, image features may contain concepts (definitions of things) and relations between concepts. This makes up a knowledge database used for object prediction.

Important to note about the almost obvious result in the use of optimization techniques and how much it differs from, for example, the much well known K-means algorithm: the optimization technique will, theoretically, always find a better solution. Let *single* be an algorithm that finds one solution; let *multi* be an algorithm based on *single* that executes it about 100 times; from the 100 times, *multi* finds the better solution. It is possible that the *single's* solution is the same found by *multi*, but optimization techniques tend to actually see the problem by the worst side, i.e. if there is a *local best* maybe there is a *global best*. This behavior demonstrates the *expectation-exploitation* dilemma. As we will see in Section 4, most of the Natural Computing techniques are based on some common facts:

a. A population can achieve better results than one individual [of that population];
b. Every population needs some sort of change in its life. It is called progress or evolution;
c. The evolution can obey a random process, sometimes called mutation, and it can occur when a population tend to remain unchanged for a long period of time;
d. Every population has an individual that knows a very good solution. Sometimes, this individual can be crossed over another individual (that knows a good solution too) to generate another, eve better individual;
e. It is also a good approach to select the most capable individuals from one population (parents), cross over them, and create the next generation of individuals (descendants). It is assumed that every generation is better than the previous one;
f. There is a method to calculate how good an individual is, to measure it. It is often called *fitness function*.

This chapter is located in this context of optimization techniques. We present some techniques to solve clustering and image segmentation problems and discussion about experiments and results.

4. Natural computing

According to (Castro, 2007) Natural Computing is the computational version of the process of extracting ideas from nature to develop computational systems, or using natural materials to perform computation. It can be classified in (Castro, 2007):

a. **Computing inspired by nature**: algorithms take inspiration from nature to solve complex problems;
b. **The simulation and emulation of nature by means of computing**: a synthetic whose product mimics natural phenomena;
c. **Computing with natural materials**: the use of novel materials to perform computation to substitute or complement silicon-based computers.
d. Next section presents some of the most representative approaches.

4.1 Artificial Neural Networks (ANN)

An Artificial Neural Network, as found in (Haykin, 1998), is a massively distributed parallel built-in processor composed of simple processing units (the neurons) that act, naturally, to store useful knowledge which is acquired through a learning process that yields better results when the processing units work in a network interconnected form (the neural network).

The learning process, realized through a learning algorithm, resembles brain in two aspects:

a. Knowledge is obtained by the network from its environment through a learning process, which means the network does not acts in an unknown environment. ANN fits in a class of algorithms that need an instructor, a professor, who identifies and models the domain, presents data to the network and evaluate obtained results;
b. Forces connecting neurons, the synapse, are used to store achieved knowledge.

Some useful properties of ANN are:

1. Non-linearity
2. Mapping between Input-Output
3. Adaptability
4. Fault-tolerance
5. Uniformity of analysis and project

4.2 Evolutionary computing

The ideas of evolutionary biology and how descendants carry on knowledge from their parents to be adaptive and better survive are the main inspiration to develop search and optimization techniques for solving complex problems.

Evolutionary Algorithms have their bases on biology and, specifically, Evolutionary Theory and adapting organisms. (Castro, 2007) says that this category of techniques are based on the existence of a population of individuals that are capable of reproduction and are subject to genetic variation, followed by selection of new more adapted individuals in its environment.

There are many variations in the concept of Evolutionary Algorithms:

a. Genetic Algorithms
b. Evolutionary Strategies
c. Evolutionary Programming and
d. Genetic Programming

Although, they are all based on the following principles:

a. A population of individuals reproduces and transmits characteristics to other generations (inheritance). This concept determines that every individual, called *chromosome* carries a potential solution to the optimization problem in question. The solution represents the *genetic trace* of the individual, the chromosomes' components, the *alleles*, and it's encoded and structured in some way. These individuals are capable of reproduction, which is, a combination between two individuals and, after this process, future generation carry characteristics of previous ones.
b. Genetic variation: the individual reproduction mechanism generates modifications in the genetic trace of the next population's individuals. A process known as *mutation* allows the exploration of new solutions inside the search space.
c. Natural selection: the living environment for individuals is competitive, for only one of them will give a most adequate and useful solution to a given problem. So, it's necessary to define some way to verify how much an individual is able to participate in the process of generation of new individuals. The evaluation is realized through a performance evaluation function, known as *fitness function*.

It is important to remember that some characteristics of living organisms are not present in the formulation of evolutionary methods. (Bar-Cohen, 2006) presents some of them:

a. In nature, the occurrence of climate variations and environmental situations changes the characteristics of species through time and are fundamental to the verification of how much skilled an organism is. Evolutionary algorithms, otherwise, consider that the fitness function is constant in time.
b. In natural evolution, individuals of different species can battle and only one will survive. In evolutionary algorithms there is only one species.

In summary, with bases in (Krishna & Murty, 1999) an evolutionary algorithm is composed of the following steps:

1. Initialization of Population or Initial Generation: is often a random process to generate individuals for the initial population.
2. Selection: chromosomes of a previous population are selected to be part of the reproduction process. In general, a probabilistic distribution is used and the selection is based in the value of the fitness function for every individual.
3. Mutation: the individual's encoded solution, the allele, generated in the reproduction process, is exchanged in some way to make the algorithm don't stay stuck on *local optima*, but, through an exploration process, stay next to the *global optima*.

This process of generation of new individuals and population modification or update is repeated several times, until a stop criterion is satisfied.

Some applications of evolutionary algorithms are:

- Planning (i.e.: routing and scheduling)
- Design (i.e.: signal processing)
- Simulation and identification
- Control
- Classification (i.e.: machine learning, pattern recognition)

4.3 Swarm intelligence

Optimization based on swarm intelligence corresponds to methods that have become target of recent scientific researches. (Brabazon & O'Neill, 2006) indicates that there are two variations of this swarm model:

a. The first is inspired in bird flock social behavior
b. The second is based on behavior of insects, like ants.

The term "swarm intelligence" can have many definitions. (Castro, 2007) quotes some of them:

- Swarm intelligence is a property of non-intelligent agent systems with limited individual capabilities that exhibit collective intelligent behavior (White & Parurek, 1998).
- Swarm intelligence includes every effort to design algorithms or distributed devices to solve problems inspired in collective behavior or social insects and other animal societies (Bonabeau et al., 1999).

Ant Colony Optimization (ACO) was designed in 1997 by Dorigo and collaborators. They showed how the behavior of ants following pheromone could be used to optimize Travelling Salesman Problem (TSP) (Kennedy & Eberhart, 2001). For a detailed presentation of this method, please refer to (Brabazon & O'Neill, 2006).

Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 2001) is a population based stochastic algorithm, modeled after the observation and bird flock behavior simulation. Even being very similar to other evolutionary approaches, PSO defines that each individual (called *particle*) benefits from its own previous solutions (a notion of history) (Omram, 2004).

The theory that delineates PSO design is under the Adaptive Culture Model and three fundamental principles are taken into account:

a. **To evaluate**: learning is based on the analysis that every individual make of its own responses to external stimuli.
b. **To compare**: individuals are stimulated to compare themselves to other individuals, mainly that ones who have better performance and success.
c. **To imitate**: the logical consequence of the previous principles, it directs the individuals on their learning process.

4.3.1 The algorithm

The classical PSO design is that each particle, amongst the multitude of individuals (the swarm), flies through the search space (Omram, 2004) and carries on a potential solution to the optimization problem (Omram et al., 2006). The movement of each particle, which is, the changing of position, is determined by an equation that considers he current position of the particle and a velocity vector (Omram, 2004; Omram et al., 2006):

$$\mathbf{x}_i = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \tag{9}$$

$$\mathbf{v}_i(t+1) = \varpi \mathbf{v}_i(t) + c1r1\left(\mathbf{p}_i(t) - \mathbf{x}_i(t)\right) + c2r2\left(\mathbf{p}_g(t) - \mathbf{x}_i(t)\right) \tag{10}$$

where, according to (Omram et al., 2006):

a. ω is the inertia weight, which controls the impact of the previous velocity
b. *c1* and *c2* are acceleration constants
c. r*1*~U(*0,1*) and r2~U(*0,1*)
d. U(*0,1*) is a uniform distribution between 0 and 1

e. $\mathbf{p}_i(t)$ is the *cognitive component*, which represents the experience of particle i about where is the best solution. It considers the memory of particle's previous solutions
f. $\mathbf{p}_g(t)$ is the *social component*, which represents the experience of the whole swarm about where is the best solution

A user defined maximum velocity can be used to constraint the velocity update (Kennedy & Eberhart, 2001). The performance of the particle is measured using a fitness function which depends on the optimization problem.
The PSO algorithm is summarized as follows:

1. For each particle, randomly position it in the search space and randomly initialize its velocity vector
2. Repeat while until a stop criterion is satisfied
   a. For each particle
      i. Evaluate its quality (using the fitness function)
      ii. Update its best position
      iii. Update swarm's best position
      iv. Update its velocity (Eq. 10)
      v. Update its position (Eq. 9)

4.4 Artificial Immune Systems

Artificial Immune Systems (AIS) is a term to adaptive systems, emerging in 1980's, that extract ideas and metaphors from the biologic immune system to solve computer problems (Castro, 2007).
The main idea is inspired in following understanding (Castro, 2007):

a. that every living organism have the ability to resist over illness caused by pathogenic agents (virus or bacteria)
b. the first rule of the immune system is to protect the body or structure of the living organism; the cells of the immune system are capable to recognize molecular patterns (some sort of molecular signature) that is present within pathogens
c. once the pathogen is recognized, cells send each other signals that indicates the need for fight against the illness

This framework of immunologic engineering is composed by (Castro, 2007):

a. a representation of the system's components
b. a set of mechanisms to evaluate the interaction between individuals and their environment. The environment is simulated by a series of stimuli (input patterns), one or more evaluation functions (fitness)
c. adaptive procedures rule the system dynamics, which is, how its behavior changes over the time.

As can be seen, there is a very large set of naturally inspired approaches, each one needing its own chapter to be clearly detailed. This chapter will focus on Genetic Algorithms and Particle Swarm Optimization.

5. Clustering and image segmentation based on natural computing

This section presents two clustering methods based on GA and PSO, both used in clustering and image segmentation.

5.1 Genetic K-means algorithm

Genetic Algorithms have been applied to many function optimization problems and are shown to be good in finding optimal and near optimal solutions (Krishna & Murty, 1999). Aiming to solve the partitional clustering algorithm problem of finding a partition in a given data, with a number of centroids (or clusters), Genetic K-Means Algorithm (GKA) is introduced by (Krishna & Murty, 1999); it establishes an evaluation criterion based on the minimization of the *Total Within Cluster Variation* (TWCV), an objective function that is defined as follows (Doi, 2007; Lu et al., 2004): given **X**, the set of N patterns, and X_{nd} the dth feature of a pattern Xn, G_k the kth cluster and Z_k the number of patterns in G_k, the TWCV is defined as:

$$TWCV = \sum_{n=1}^{N}\sum_{d=1}^{D} X_{nd}^{\ 2} - \sum_{k=1}^{K}\frac{1}{Z_k}\sum_{d=1}^{D} SF_{kd}^{\ 2} \tag{11}$$

where SF_{kd} is the sum of the dth features of all patterns in G_k. The TWCV is also known as *square-error measure* (Krishna & Murty, 1999). The objective function, thus, tries to minimize the TWCV, finding the clustering that has centroids attending concepts of (Omram et al., 2006) *compactness* (patterns from on cluster are similar to each other and different from patterns in other clusters) and *separation* (the clusters' centroids are well-separated, considering a distance measure as the Euclidean Distance). It is found in (Bandyopadhyay & Maulik, 2002) another method for genetic algorithm based clustering that uses another fitness function, the Davies-Boudin index, which is a function of the ration of the sum of within-cluster scatter to between-cluster separation. As will be seen later, other validation indexes may be used and despites the objective function, GKA main aspects are:

1. **Coding**. Refers to how to encode the solution (the chromosome); one way of doing this is the *string-of-group-numbers encoding* where for Z coded solutions (partitions), represented by strings of length N, each element of each string (an allele) contains a cluster number.
2. **Initialization**. The initial population P_0 is defined randomly: each allele is initialized to a cluster number. The next population P_{i+1} is defined in terms of the selection, mutation and the K-means operator.
3. **Selection**. Chromosomes from a previous population are chosen randomly according to a distribution.
4. **Mutation**. The mutation operator changes an allele value depending on the distances of the cluster centroids from the corresponding pattern.
5. **K-Means Operator (KMO)**. This operator is used to speed up the convergence process and is related to one step of the classical K-means algorithm. Given a chromosome, each allele is replaced in order to be closer to its centroid.

Another approach, K-Means Genetic Algorithm (KGA), is presented in (Bandyopadhyay & Maulik, 2002) and shows a slight modification to the definitions presented before: the crossover operator is added to the algorithm and it is a probabilistic process that exchanges information between two parent chromosomes for generating two new (descendant) chromosomes.

5.2 Clustering using Particle Swarm Optimization

Different approaches are found that implement clustering based PSO algorithms, such as (Omram et al., 2006) and (Omram, 2004). A PSO-based Clustering Algorithm (PSOCA) can be defined as follows (Omram, 2004; Omram et al., 2006): in the context of data clustering, a single particle represents de set of K cluster centroids, in other words, each particle represents a solution to the clustering problem and, thus, a swarm represents a set of candidate data clusterings. The main steps are:

a. Initialize particle position and velocity (for each particle);
b. While a stop criterion is not found, for each particle:
    a. Calculates particle's quality
    b. Finds particle's best and global best
    c. Updates particle's velocity.

6. Experiments and results

The experiments rely on evaluate numerical results of clustering algorithms based on Genetic Algorithms and PSO. As previously seen, both methods are modeled to allow a switch of the traditional and basic clustering algorithm. Thus, this allows us to define the following algorithms variations:

a. Genetic K-means Algorithm (GKA)
b. Genetic Fuzzy C-means Algorithm (GFCMA)
c. PSO-based K-means Algorithm (PSOKA)
d. PSO-based Fuzzy C-means Algorithm (PSOFCMA)

The datasets used in data clustering experiments are the following:

a. **Ruspini**: two-dimensional dataset with 75 patterns. Has four classes easily separable
b. **Wine**: thirteen dimensions and 178 patterns. Has three classes
c. **Iris**: four-dimensional dataset with 150 patterns. Has three classes

Implementation was made in Matlab and used the Fuzzy Clustering and Data Analysis Toolbox (Balasko et al., 2005).

To best evaluate the results, considering classification error, in each dataset was added another dimension, corresponding to the cluster number associated to the pattern. Cluster Validation Indexes (CVI) was used to obtain numerical results and guide the possible best solution found by the algorithms: Davies-Bouldin (DB), SC (separation and compactness), S (separation), and Xie-Beni (XB). For a review on CVI please refer to (El-Melegy et al., 2007).

To compare the effectiveness of GA and PSO-based approaches, Table 1 presents K-means and FCM clustering results for Ruspini, Wine and Iris datasets. It can be seen that FCM performs better than K-means considering the CVI and Error of classification.

Table 2 presents GKA and GFCMA clustering results for Ruspini, Wine and Iris datasets. It can be seen that, in general, GKA got better results than K-means, FCM and GFCMA.

CVI	K-Means			FCM
	Min	**Mean**	**Max**	**-**
DB	0.61212	0.69081	0.77991	0.62613
SC	0.46308	0.48372	0.51758	0.62798
S	0.00446	0.00465	0.00497	0.00638
XB	3.41458	4.47178	4.93836	3.97634
Error (%)	11.33	19.60	42.67	10.67

(a)

CVI	K-Means			FCM
	Min	Mean	Max	-
DB	0.29046	0.44717	0.87690	0.33632
SC	0.27625	0.35350	0.51807	0.36330
S	0.00407	0.00665	0.01296	0.00541
XB	2.88926	7.18313	8.57401	6.04515
Error (%)	0.00	30.43	100.00	0.00

(b)

CVI	K-Means			FCM
	Min	Mean	Max	-
DB	1.10551	1.26082	1.57878	1.30418
SC	0.95495	0.97880	1.25538	1.62948
S	0.00664	0.00682	0.00859	0.01197
XB	1.90714	1.96253	2.17519	0.97245
Error (%)	2.81	6.19	47.75	5.06

(c)

Table 1. Clustering results for K-means and FCM: (a) Iris; (b) Ruspini; (c) Wine

CVI	GKA			GFCMA		
	Min.	Mean	Max.	Min.	Mean	Max.
DB	0.58931	0.61651	0.66188	0.45831	0.62613	0.64908
SC	0.43933	0.45049	0.45839	0.62725	0.62947	0.63466
S	0.00389	0.00416	0.00458	0.00630	0.00638	0.00644
XB	2.50475	2.58308	2.68649	1.35521	1.63055	1.85673
Error (%)	10.67	32.39	68.00	10.00	15.42	55.33

(a)

CVI	GKA			GFCMA		
	Min.	Mean	Max.	Min.	Mean	Max.
DB	0.29046	0.29046	0.29046	0.29046	0.32035	0.32237
SC	0.27625	0.27625	0.27625	0.36330	0.36332	0.36339
S	0.00407	0.00407	0.00407	0.00540	0.00541	0.00542
XB	2.81341	2.90996	3.04789	0.77498	1.28165	1.95288
Error (%)	0.00	11.56	100.00	0.00	7.19	76.00

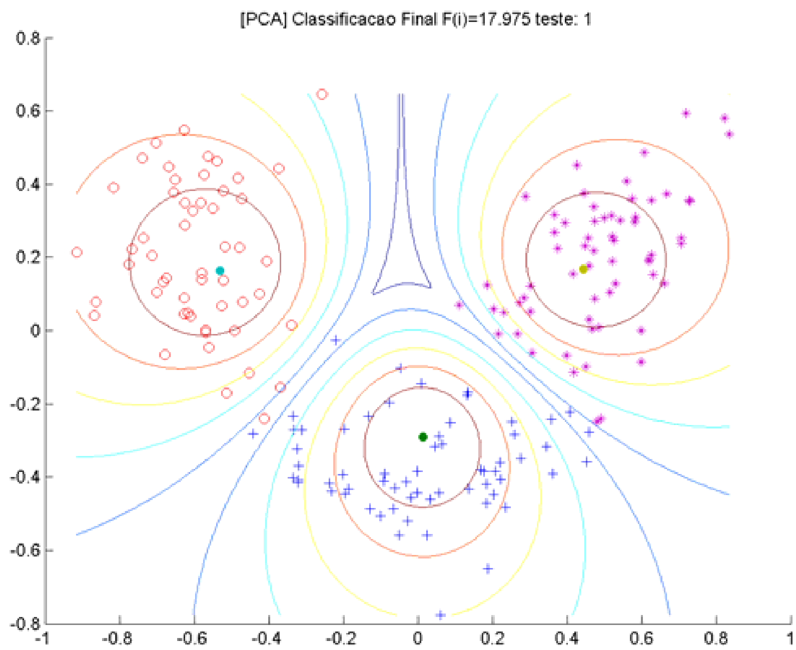
(b)

CVI	GKA			GFCMA		
	Min.	Mean	Max.	Min.	Mean	Max.
DB	1.10055	1.10605	1.29697	0.84352	1.11319	1.30337
SC	0.96569	0.96961	0.97382	1.62937	2.41962	5.31974
S	0.00670	0.00674	0.00680	0.01197	0.01913	0.04760
XB	1.52923	1.58911	1.63309	0.60118	0.60694	5.31974
Error (%)	3.37	9.11	23.03	5.06	17.10	53.37

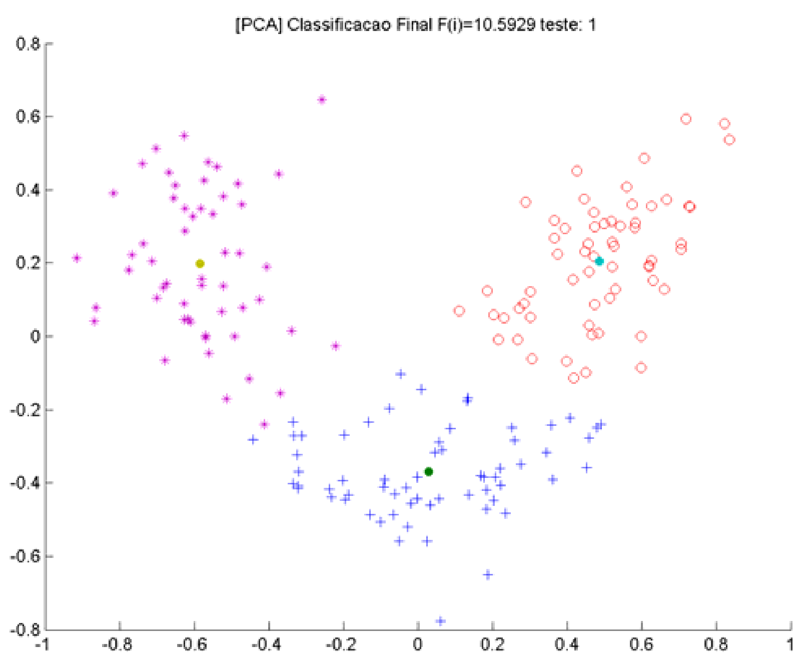
(c)

Table 2. Clustering results for GKA and GFCMA: (a) Iris; (b) Ruspini; (c) Wine

Fig. 1 shows clustering results for Wine dataset using GFCMA and GKA methods (PCA is used to reduce dimensions) obtaining error rate of 5.05% and 4.5%, respectively.



(a)



(b)

Fig. 1. GA clustering results for Wine dataset: (a) GFCMA; (b) GKA

CVI	PSOKA			PSOFCMA		
	Min.	Mean	Max.	Min.	Mean	Max.
DB	0.27045	0.36780	0.52796	0.57841	0.62335	0.62613
SC	0.39613	0.47915	0.54635	0.62484	0.62749	0.62796
S	0.00365	0.00421	0.00516	0.00637	0.00637	0.00638
XB	1.19575	1.52560	2.06278	1.21399	1.37726	1.68562
Error (%)	6.00	65.97	100.00	10.67	15.75	35.33

(a)

CVI	PSOKA			PSOFCMA		
	Min.	Mean	Max.	Min.	Mean	Max.
DB	0.00471	0.00489	0.29046	0.00538	0.00540	0.00541
SC	0.29046	0.30640	0.33533	0.29046	0.30042	0.32035
S	0.00832	0.71131	1.68594	0.36314	0.36328	0.36330
XB	0.18273	1.01053	1.75728	0.80723	1.44156	3.27777
Error (%)	0.00	22.25	100.00	0.00	9.81	92.00

(b)

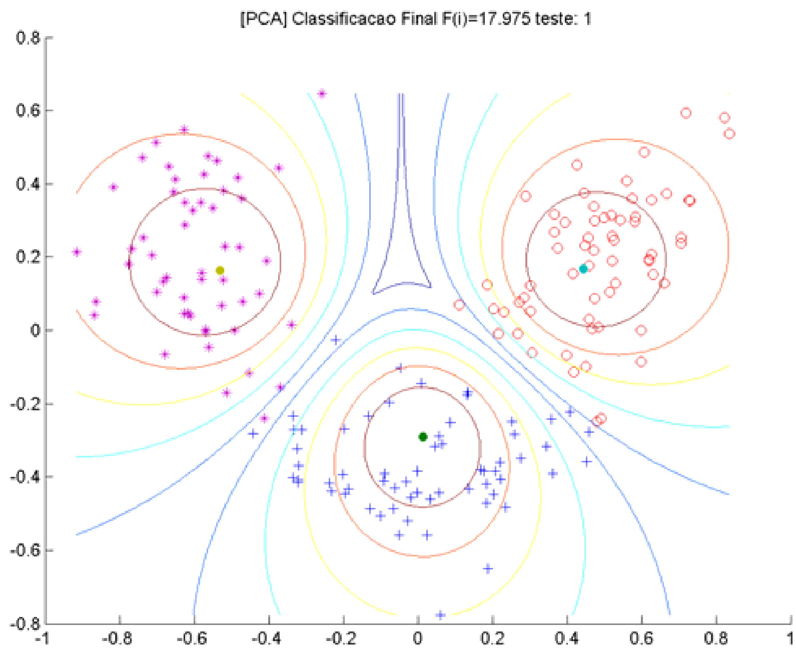
CVI	PSOKA			PSOFCMA		
	Min.	Mean	Max.	Min.	Mean	Max.
DB	0.23707	0.69798	1.02811	0.86679	1.10988	1.30337
SC	0.79707	0.95203	1.22435	1.62937	1.62937	1.62937
S	0.00479	0.00672	0.00870	0.01197	0.01197	0.01197
XB	1.19477	1.36998	1.54367	0.59022	0.60331	0.61588
Error (%)	5.06	31.25	72.47	5.06	13.80	49.44

(c)

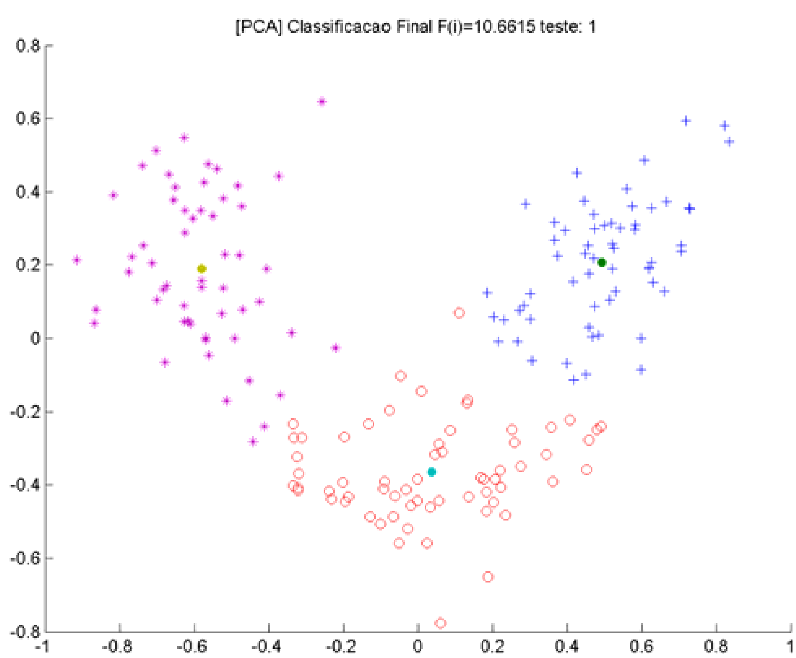
Table 3. Clustering results for PSOKA and PSOFCMA: (a) Iris; (b) Ruspini; (c) Wine

Table 3 summarizes clustering results for PSOKA and PSOFCMA. It can be seen that PSOKA performs better than PSOFCMA considering CVI and PSOFCMA is better than PSOKA considering Error (error of classification). Fig. 2 presents PSOFCMA and PSOKA clustering for Wine.

The dataset used in image segmentation experiments was obtained from the BrainWeb system (BrainWeb, 2010; Cocosco et al., 1997; Kwan et al., 1996; Kwan et al., 1999; Collins et al., 1998), it corresponds to simulated MR images of T1 modality, 0% noise, and 0% intensity. BrainWeb dataset contains 10 classes that range from background to connective material. For ground truth and classification error evaluation is used the "crisp" dataset. Fig. 3 presents a slice from the MRI Volume in BrainWeb that is used as dataset for experiments. Fig. 3a represents the input to algorithms. Fig. 3b represents the ground truth. Image segmentation approaches of current work are unsupervised, so the ground truth is used only as a final evaluation step, to quantify image segmentation results.

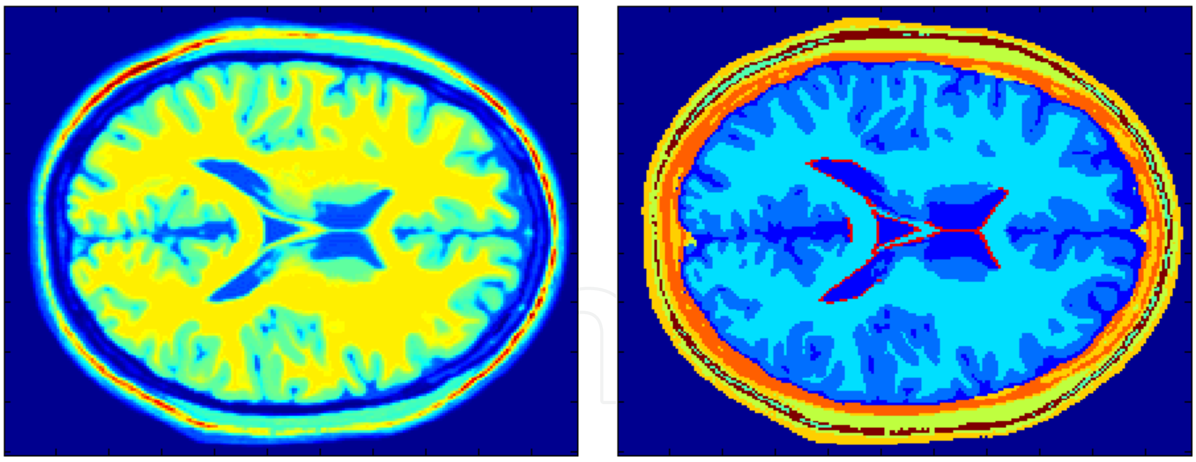


(a)



(b)

Fig. 2. PSO clustering results for Wine dataset: (a) PSOFCMA; (b) PSOKA



(a) (b)

Fig. 3. Slice from volume in BrainWeb dataset: a) fuzzy dataset; b) crisp dataset

Final objective is to find the correct classes that represent brain regions. Fig. 4 shows crisp dataset in detail and with every class individually.

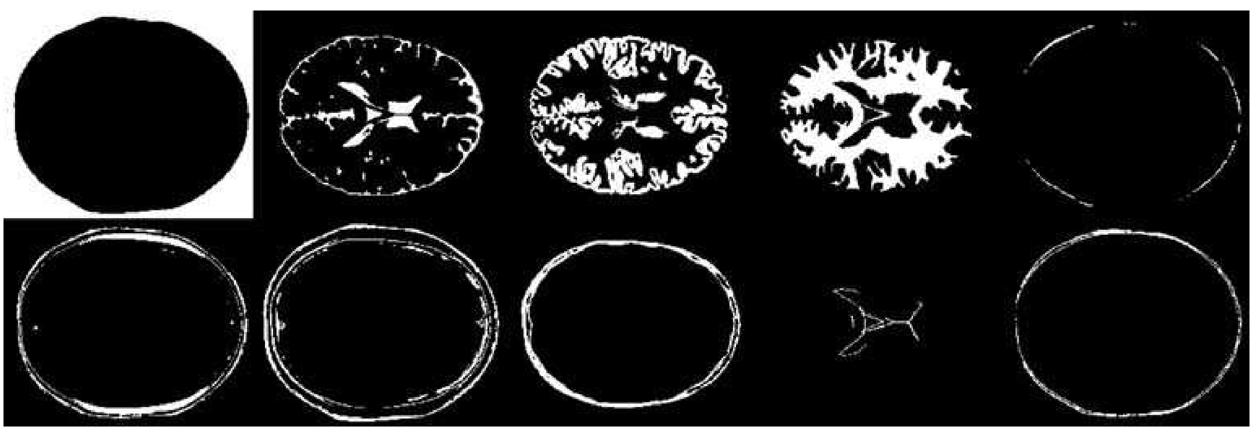


Fig. 4. Crisp dataset in detail: every class corresponding to one brain region in BrainWeb

Cluster Validation Indexes are commonly used to evaluate image segmentation, but results did show that classification error was not acceptable – experiments did show it was around 90%. From this assumption, another study has begun in the direction of finding a better way to evaluate image segmentation. (Chabrier et al., 2006) work on unsupervised image segmentation evaluation methods present several approaches. Amongst them we use the Rosenberger's evaluation criterion, which is defined by following equation (Chabrier et al., 2006):

$$ROS(I_R) = \frac{1 + \frac{1}{C_{N_R}^2} \sum_{i,j=1,i\neq j}^{N_R} \left(\left| \overline{g}_I(R_i) - \overline{g}_I(R_j) \right| / 512 - 4/255^2 N_R \right) \sum_{i=1}^{N_R} \sigma^2(R_i)}{2} \qquad (12)$$

where:

a. I_R corresponds to the segmentation result of image I in a set of regions $R = \{R_1, ..., R_{N_R}\}$ having N_R regions

b. $\overline{g}_I(R_i)$ can be generalized to a feature vector computed on the pixels values of the region R_i. The same occurs for $\overline{g}_I(R_j)$

c. $C_{N_R}^2$ is the number of combinations of 2 regions among N_R

According to (Chabrier et al., 2006) this criterion combines intra and interregions disparities: intraregion is computed by the normalized standard deviation of gray levels in each region; interregions disparity computes the dissimilarity of the average gray level of two regions in the segmentation result.

For comparison purposes experiments were taken for classical K-means and Fuzzy C-means (FCM) algorithms, considering 100 rounds – with maximum 100 iterations each. Table 4 presents best results considering lower classification error.

Measure	K-means			FCM
	Min.	*Mean.*	*Max.*	--
DB	**0.33098**	0.39152	0.47994	0.38630
MSE	**39.47764**	181.26347	749.88781	86.35377
SC	0.15269	0.20480	**0.27183**	0.29905
S	1.00000	4.32406	**10.00000**	0.00001
XB	**141.13651**	997.30277	26302.67634	145.14488
ROS	**0.50030**	0.50036	0.50042	0.50039
Error (%)	**50.21514**	65.40306	84.72134	68.78071

Table 4. Image Segmentation results for K-means and FCM

Important to note is that there were no heuristics for experiments with K-means and FCM: values from Table 4 are obtained may be different every time the experiment runs, unless for FCM, for it has the same results have always been found.

Fig. 5 and Fig. 6 show qualitative results for K-means and FCM, respectively.

Both image segmentations using K-means and FCM shows that all classes have many classification errors and many of them are indistinguishable from each other. In other words, most classes are very similar.

Current work's objective is that approaches under investigation (GKA, GFCMA, PSOKA and PSOFCMA) achieve better values for all measures and classification error. Each method runs in a set of experiments, which evaluate the effect of some parameters:

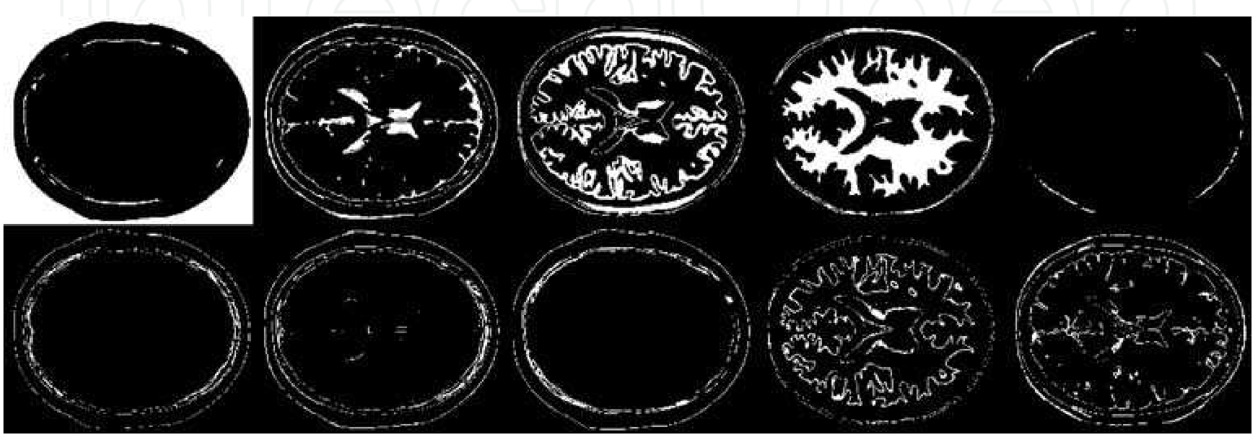


Fig. 5. Crisp dataset in detail: every class corresponding to one brain region in BrainWeb

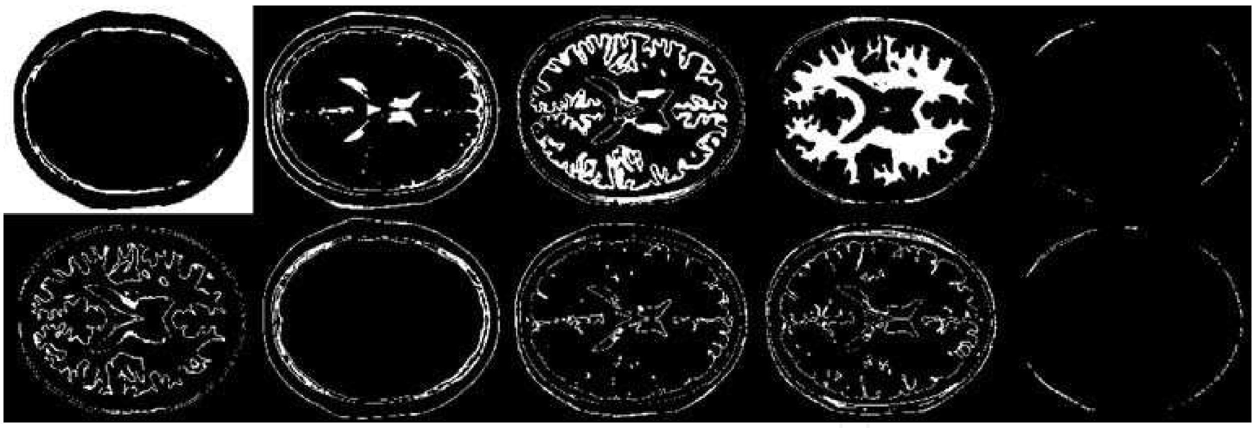


Fig. 6. Crisp dataset in detail: every class corresponding to one brain region in BrainWeb

a. Parameters for GKA and GFCMA
- Crossover rate
- Mutation rate
- Number of generations
- Population size

b. Parameters for PSOKA and PSOFCMA
- Maximum velocity
- Number of individuals in swarm

For each approach the fitness function is based on one of measures: Cluster Validation Indexes, MSE or ROS. This can be considered a parameter to the algorithm as well. Some measures need to be minimized (DB, MSE, XB, ROS) and others need to be maximized (SC, S). It is important to note that current approaches are unsupervised. This means that obtaining classification error has no influence on approaches' behavior and is used only as a way to evaluate its performance in a controlled scenario.

Based on observations from experiments, GKA and GFCMA experiments evaluate best when they use crossover rate of 70%, mutation rate of 0.5% and number of generations around 100. Higher numbers of generation values have no influence. Population size is of 10 individuals. Numerical results for GKA and GFCMA are shown by Table 5.

Measure\Algorithm	GKA		GFCMA	
	Value	Error	Value	Error
DB	**0.30636**	63.53082	0.34955	66.07175
MSE	**12.40774**	66.08193	74.99295	72.4037
SC	0.42729	68.42427	**0.90113**	48.82756
S	0.00002	72.61756	**0.00007**	51.29974
XB	124.14228	66.22705	**84.06929**	72.45716
ROS	0.50026	63.51045	**0.50025**	**40.63447**

Table 5. Image Segmentation results for GKA and GFCMA

According to results from Table 5 it is noted that GFCMA experiment with ROS measure outperforms other experiment's configurations – considering classification error. Fig. 7 shows classes for GFCMA's experiment that achieved best results.

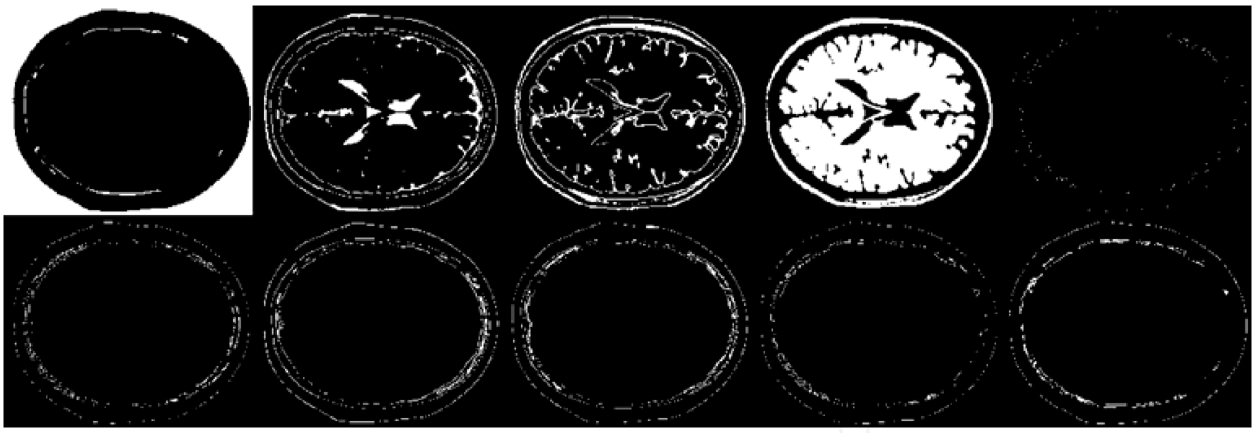


Fig. 7. Crisp dataset in detail: every class corresponding to one brain region in BrainWeb

PSOKA and PFOFCMA experiments use a maximum velocity parameter equals to 0.2 and stops when stabilization is found (value of objective function does not change across 10 iterations). Table 6 shows numerical results for PSOKA and PSOFCMA.

Measure\Algorithm	PSOKA		PSOFCMA	
	Value	Error	Value	Error
DB	0.34345	71.69336	**0.33365**	65.24938
MSE	**14.26504**	72.21529	74.46232	69.18044
SC	0.77279	66.34926	**0.99548**	71.43621
S	**0.00007**	68.00163	0.00004	71.37001
XB	260.60458	**60.57489**	**94.1416**	68.5312
ROS	**0.50018**	66.03356	0.50030	68.31479

Table 6. Image Segmentation results for PSOKA and PSOFCMA

Table 6 shows that PSOKA experiment with XB measure got lower classification error. Fig. 8 shows brain regions for PSOKA's experiment that achieved best results.

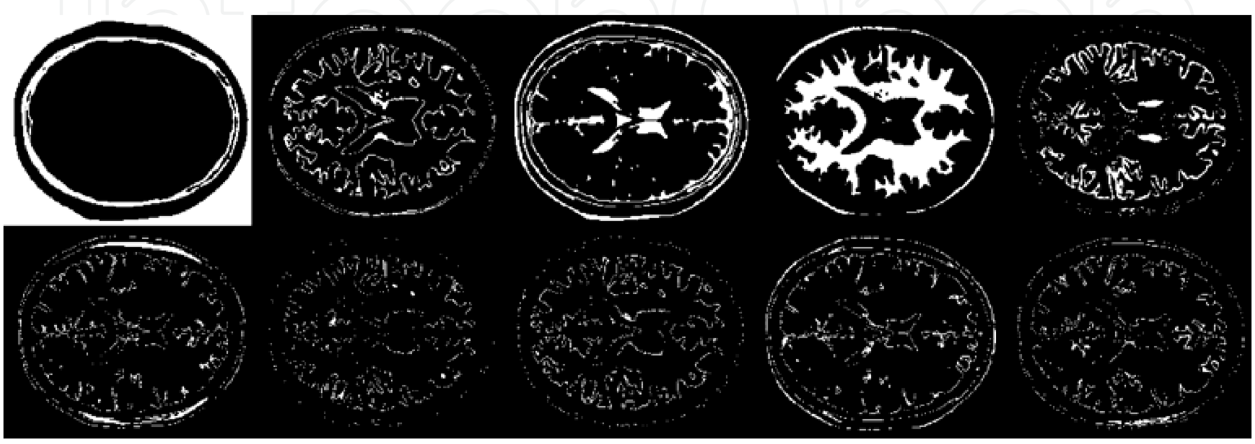


Fig. 8. Crisp dataset in detail: every class corresponding to one brain region in BrainWeb

Experiments with BrainWeb dataset had the ground truth to evaluate the approaches and used gray scale images. To show the performance of approaches with general purpose images, we will segment color images: Lena, Peppers and Duck.

(a) (b) (c)

Fig. 9. Color images: a) Lena; b) Peppers; and c) Duck

Results will show segmentation results considering each approach and all quality measures. The number of clusters proceeds as follows: Lena – 6 classes; Peppers – 5 classes; and Duck – 3 classes. Image has been resized to 96 x 96 pixels, RGB color. Tables 7 to 9 and Figures 10 to 12 present quantitative and qualitative image segmentation results, respectively. For these datasets there is no ground truth (no true labels). Thus, the evaluation about how measure/approach has the best result need to be made through quantitative and qualitative results. Best quantitative results are bolded in tables. Best qualitative results are harder to analyze, so the methodology is to consider:

a. For Peppers image: well defined frontiers and region homogeneity
b. For Lena image: well defined frontiers between skin, hat and hair and region homogeneity
c. For Duck image: well defined frontiers between duck body, mouth and glasses/ background

This criterion is used to qualitatively evaluate image segmentation results. Considerations about the results are presented in next section.

Measure\Algorithm	GKA	GFCMA	PSOKA	PSOFCMA
DB	0.56110	0.56504	**0.54677**	0.6147
MSE	**211.10835**	651.25003	239.515	640.409
SC	1.47962	**8.50041**	1.4389	8.09223
S	0.00017	**0.00140**	0.00032	0.00087
XB	8.67126	**3.70102**	5.69572	4.11349
ROS	0.49947	0.51484	**0.48019**	0.51205

Table 7. Image Segmentation results for Peppers image

Fig. 10. Qualitative image segmentation results for Peppers image. Rows: 1 – GFCMA, 2 – GKA, 3 – PSOFCMA, 4 – PSOKA. Columns: 1 – DB, 2 – MSE, 3 – SC, 4 – S, 5 – XB, 6 – ROS.

Measure\Algorithm	GKA	GFCMA	PSOKA	PSOFCMA
DB	0,63599	0,67499	**0,44408**	0,62798
MSE	**105,67107**	373,08084	114,80000	369,99500
SC	0,89346	**10,49051**	1,21201	4,71058
S	0,00012	**0,00112**	0,00023	0,00052
XB	11,58644	6,47175	7,62521	**5,82961**
ROS	0,54312	0,54141	**0,53541**	0,54345

Table 8. Image Segmentation results for Lena image

Fig. 11. Qualitative image segmentation results for Lena image. Rows: 1 – GFCMA, 2 – GKA, 3 – PSOFCMA, 4 – PSOKA. Columns: 1 – DB, 2 – MSE, 3 – SC, 4 – S, 5 – XB, 6 – ROS.

Measure\Algorithm	GKA	GFCMA	PSOKA	PSOFCMA
DB	0,43669	0,44730	**0,30422**	0,44495
MSE	**260,16469**	542,49030	347,33520	536,90780
SC	1,05008	**4,85890**	1,08519	29,61981
S	0,00021	**0,00243**	0,00019	0,00081
XB	9,32596	6,74430	**1,83358**	7,99377
ROS	**0,46663**	0,56625	0,50669	0,58084

Table 9. Image Segmentation results for Duck image

Fig. 12. Qualitative image segmentation results for Duck image. Rows: 1 – GFCMA, 2 – GKA, 3 – PSOFCMA, 4 – PSOKA. Columns: 1 – DB, 2 – MSE, 3 – SC, 4 – S, 5 – XB, 6 – ROS.

7. Conclusion and future research

The present work presents two natural computing methods for data clustering and image segmentation, their implementation and some results, one based on Genetic Algorithms and the other based on Particle Swarm Optimization. The task of image segmentation is not a trivial process. Considering the medical imaging context it is highly important the specialist's opinion about the results found. As the MRI dataset is simulated the experiments were guided by this situation. Thus, it is necessary to make experiments with real MRI imagery. Color images were used as well to analyze the performance of approaches on general purpose image segmentation.

The methodology used in this work was based on the following:

1. To implement the algorithms
2. To evaluate clustering results on known databases
3. To use the obtained results to guide tests with image segmentation. Image segmentation tests must consider image characteristics.

As the present methods are based on Evolutionary Computation and all have a performance (fitness) function, there must be some way to guide this evolution, so tests were made considering several Clustering Validation Indexes (DB, SC, S and XB), a commonly used error measure (MSE) and an image segmentation specific measure (ROS). Also, when available, a measure of classification error was used to identify the method's final and overall performance. CVI, MSE and ROS can be used as a function of quality of a solution (population/generation for GKA or particle for PSO).

Considering classical clustering, K-means outperforms FCM considering classification error. Qualitative analysis shows that both algorithms did not identify correctly any of the classes and it is dificult to evaluate the quality of solution because, according to ground truth, most classes are merged or part of one class is in other class. Class 1, which may be background is the most correctly identified, even having some elements from other class in its interior. Classes 2 and 4 are almost correct also.

Considering GA, the lower classification error was obtained by GFCMA (around 40%), with ROS index. GFCMA also got best results considering SC, S, XB and ROS measures. Qualitative result shows that the same considerations for K-means and FCM apply to GFCMA, but most classes are almost identical, which results in weak qualitative evaluation. The quantitative measures were also enhanced. Only index S was better with K-means.

Considering PSO, the lower classification error was obtained by PSOKA (around 60%), with XB index. PSOKA was better considering MSE, S and ROS, while PSOFCMA was better considering DB, SC and XB. Curiously, better value of XB was not the one that obtained lower classification error. PSO also enhanced quantitative measures.

MRI dataset evaluation has considered the ground truth, so it was possible to evaluate experiment's results considering classification error. Experiments were made to evaluate the performance of GA and PSO considering general purpose color images. For Peppers image, GFCMA got best quantitative results (indexes SC, S and XB), followed by PSOKA (indexes DB and ROS). Qualitative analysis shows that GFCMA with index DB got best results, considering that red and green peppers where correctly separated and GFCMA also identify some background (between peppers). For Lena image, GFCMA (indexes SC and S) and PSOKA (indexes DB and ROS) got best results. Qualitative analysis shows that all approaches had problems with regions of hat and skin. Considering skin and hair, GFCMA with ROS index and PSOKA with ROS index got best results. For Duck image, GKA (indexes MSE and ROS), GFCMA (indexes SC and S) and PSOKA (indexes DB and XB) got best quantitative results. Qualitative analysis shows that GKA with index SC and S, PSOFCM with index SC and S got best results.

Most experiments using classical K-means and FCM run to 100 iterations – and more iteration could lead to lower error values. It's necessary to remember that GA and PSO both use only one iteration of K-means and FCM, and the convergence is fast (about 5 to 10 iterations). The problem of possible premature convergence of PSO is investigated by (Yong-gang, et al., 2005), which proposed the Improved PSO (IPSO) algorithm. This is a problem to take into account as a try to improve image segmentation results for PSO and GA also.

In summary, considering the results obtained from the experiments, it can be said that methods based on FCM performed better. As the present work does not evolves to image registration and classification more evaluation is necessary to argue about Fuzzy C-means superiority over K-means, in terms of the implemented algorithms. The use of image segmentation benchmarks to compare to obtained results is also a task for future research, together with studies about newer approaches and definitions for GA and PSO, mainly considering image characteristics, like texture, region and borders (frontiers).

One problem with these evolutionary algorithms is that the only concern is the quality of the solution, with little attention given to computational efficiency (Hruschka et al., 2009). The authors also analyze that the literature on clustering and image segmentation techniques based on evolutionary or natural computing does not provide detailed theoretical analyses in terms of time complexity. As we agree with this argumentation, one future work is the correct understanding of these algorithms in terms of computational efficiency and complexity.

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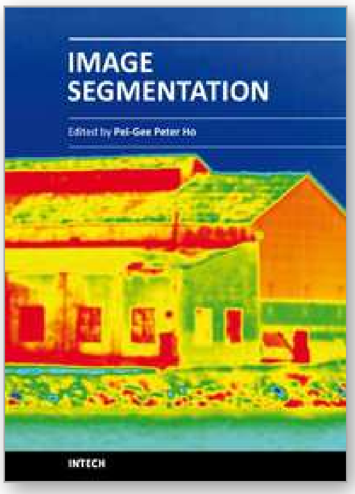

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It was estimated that 80% of the information received by human is visual. Image processing is evolving fast and continually. During the past 10 years, there has been a significant research increase in image segmentation. To study a specific object in an image, its boundary can be highlighted by an image segmentation procedure. The objective of the image segmentation is to simplify the representation of pictures into meaningful information by partitioning into image regions. Image segmentation is a technique to locate certain objects or boundaries within an image. There are many algorithms and techniques have been developed to solve image segmentation problems, the research topics in this book such as level set, active contour, AR time series image modeling, Support Vector Machines, Pixon based image segmentations, region similarity metric based technique, statistical ANN and JSEG algorithm were written in details. This book brings together many different aspects of the current research on several fields associated to digital image segmentation. Four parts allowed gathering the 27 chapters around the following topics: Survey of Image Segmentation Algorithms, Image Segmentation methods, Image Segmentation Applications and Hardware Implementation. The readers will find the contents in this book enjoyable and get many helpful ideas and overviews on their own study.

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