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Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation

Mohamad Forouzanfar [a,b,1], Nosratallah Forghani [b,*,1], Mohammad Teshnehlab [c]

[a] School of Information Technology and Engineering (SITE), University of Ottawa, 800 King Edward Avenue, Ottawa, Ontario, Canada K1N 6N5
[b] Department of Biomedical Engineering, Faculty of Electrical Engineering, K.N. Toosi University of Technology, P.O. Box 16315-1355, Tehran, Iran
[c] Department of Control Engineering, Faculty of Electrical Engineering, K.N. Toosi University of Technology, P.O. Box 16315-1355, Tehran, Iran

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ABSTRACT

A traditional approach to segmentation of magnetic resonance (MR) images is the fuzzy c-means (FCM) clustering algorithm. The efficacy of FCM algorithm considerably reduces in the case of noisy data. In order to improve the performance of FCM algorithm, researchers have introduced a neighborhood attraction, which is dependent on the relative location and features of neighboring pixels. However, determination of degree of attraction is a challenging task which can considerably affect the segmentation results.

This paper presents a study investigating the potential of genetic algorithms (GAs) and particle swarm optimization (PSO) to determine the optimum value of degree of attraction. The GAs are best at reaching a near optimal solution but have trouble finding an exact solution, while PSO's-group interactions enhances the search for an optimal solution. Therefore, significant improvements are expected using a hybrid method combining the strengths of PSO with GAs, simultaneously. In this context, a hybrid GAs/PSO (breeding swarms) method is employed for determination of optimum degree of attraction. The quantitative and qualitative comparisons performed on simulated and real brain MR images with different noise levels demonstrate unprecedented improvements in segmentation results compared to other FCM-based methods.

1. Introduction

Magnetic resonance imaging (MRI) is a technique that uses a magnetic field and radio waves to create cross-sectional images of organs, soft tissues, bone, and virtually all other internal body structures (Haacke et al., 1999). MRI possesses good contrast resolution for different tissues and has advantages over computerized tomography (CT) for brain studies due to its superior contrast properties. In this context, brain MRI segmentation has become an increasingly important image processing step in many applications, including: (i) automatic or semiautomatic delineation of areas to be treated prior to radiosurgery, (ii) delineation of tumors before and after surgical or radiosurgical intervention for response assessment, and (iii) tissue classification (Bondareff et al., 1990).

Several techniques have been developed for brain MR image segmentation among which thresholding (Suzuki and Toriwaki, 1991), edge detection (Canny, 1986), region growing (Pohle and Toennies, 2001), and clustering (Clarke et al., 1995) are the most well-known ones. Thresholding is the simplest segmentation method, where the classification of each pixel depends on its own information such as intensity and color. Thresholding methods are efficient when the histograms of objects and background are clearly separated. Since the distribution of tissue intensities in brain MR images is often very complex, these methods fail to achieve acceptable segmentation results. Edge-based segmentation methods are based on detection of boundaries in the image. These techniques suffer from incorrect detection of boundaries due to noise, over- and under-segmentation, and variability in threshold selection for the edge image. These drawbacks of early image segmentation methods, has led to region growing algorithms. Region growing is the extension of thresholding by considering the homogeneity and connectivity criteria. However, only well-defined regions can be robustly identified by region growing algorithms (Clarke et al., 1995). Since the above mentioned methods are generally limited to relatively simple structures, clustering methods are utilized for complex pathology. Clustering is a method of grouping data with similar characteristics into larger units of analysis. Expectation–maximization (EM) (Wells et al., 1996), hard c-means and its fuzzy equivalent, fuzzy c-means (FCM) algorithms (Li et al., 1993) are the typical

* Corresponding author. Tel.: +98 21 88469084; fax: +98 21 88462066.
E-mail addresses: mforo040@site.uottawa.ca (M. Forouzanfar), n_forghani@ee.kntu.ac.ir (N. Forghani), teshnehlab@eetd.kntu.ac.ir (M. Teshnehlab).

[1] The first two authors contributed equally to this work.

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methods of clustering. A main drawback of the EM algorithm is that it is based on a Gaussian distribution model for the intensity distribution of brain images, which is not true, especially for noisy images. Since Zadeh (1965) first introduced fuzzy set theory which gave rise to the concept of partial membership, fuzziness has received increasing attention. Fuzzy clustering algorithms have been widely studied and applied in various areas. Among fuzzy clustering techniques, FCM is the best known and most powerful method used in image segmentation. FCM was first conceived in 1973 by Dunn (1973) and further generalized by Bezdek (1981). It is based on minimization of an objective function and is frequently used in pattern recognition. Unfortunately, FCM does not consider the spatial information in the image space and is highly sensitive to noise and imaging artifacts. Since medical images contain significant amount of noise caused by operator, equipment, and the environment, there is an essential need for development of less noise-sensitive algorithms.

Many modifications of the FCM algorithm have been proposed to alleviate the effects of noise, such as noisy clustering (NC) (Dave, 1991), possibilistic c-means (PCM) (Krishnapuram and Keller, 1993), robust fuzzy c-means (RFCM) algorithm (Pham, 2001), and so on. These methods generally modify most equations along with modification of the objective function. Therefore, they lose the continuity from FCM, which inevitably introduce computation issues.

Yu and Yang (2005) proposed a generalized FCM (GFCM) model to unify some variations of FCM and then studied its optimality test with parameter selection. However, the variations of the FCM in this method may not have two kinds of optimality test, i.e., one based on the cluster prototypes and another one based on membership functions. It was shown in Yu and Yang (2005) that the GFCM has only the optimality test with the cluster prototype. In Yu and Yang (2007), an alternative model of GFCM, called a generalized fuzzy clustering regularization (GFCR) was proposed that can have the optimality test with membership functions. Recently, Shen et al. (2005) introduced a new extension of FCM algorithm, called improved FCM (IFCM). They introduced two influential factors in segmentation that address the neighborhood attraction. The first parameter is the feature difference between neighboring pixels in the image and the second one is the relative location of the neighboring pixels. Therefore, segmentation is decided not only by the pixel's intensity but also by neighboring pixel's intensities and their locations. However, the problem of determining optimum parameters constitutes an important part of implementing the IFCM algorithm for real applications. The implementation performance of IFCM may be significantly degraded if the attraction parameters are not properly selected. It is therefore important to select suitable parameters such that the IFCM algorithm achieves superior partition performance compared to the FCM. In Shen et al. (2005), an artificial neural network (ANN) was employed for computation of these two parameters. However, designing the neural network architecture and setting its parameters are always complicated which slow down the algorithm and may also lead to inappropriate attraction parameters and consequently degrade the partitioning performance.

In this paper, we extend the IFCM algorithm to overcome the mentioned drawbacks in segmentation of the intensity MR images. Same as in Shen et al., (2005), a neighborhood attraction is considered to exist between neighboring pixels of the intensity image. The degree of attraction depends on pixel intensities and the spatial position of the neighbors. Two parameters $\lambda(0<\lambda<1)$ and $\xi(0<\xi<1)$ will adjust the degree of the neighborhood attractions. We will then investigate the potential of genetic algorithms (GAs) and particle swarm optimization (PSO) to determine the optimum values of the neighborhood attraction parameters. We will show that both GAs and PSO are superior to the ANN algorithm especially in segmentation of noisy MR images. However, unprecedented improvements are achieved using a hybrid method combining the strengths of PSO with GAs, simultaneously. The achieved improvements of the hybrid GAs/PSO, breeding swarm (BS), method is validated both quantitatively and qualitatively on simulated and real brain MR images at different noise levels.

This paper is organized as follows. In Section 2, the traditional FCM algorithm and its improved extension called IFCM are introduced. Section 3 presents three new parameter optimization methods based on GAs, PSO, and BS. Section 3 compares our proposed algorithms with other published techniques. Section 4 contains conclusions and addresses future work.

FCM and IFCM clustering algorithms

Let $X=\{x_1, \ldots, x_n\}$ be a data set and let c be a positive integer greater than one. A partition of X into c clusters is represented by mutually disjoint sets $X_1, \ldots, X_c$ such that $X_1 \cup\cdots\cup X_c=X$ or equivalently by indicator function $\mu_1, \ldots, \mu_c$ such that $\mu_i(x)=1$ if x is in X_i and $\mu_i(x)=0$ if x is not in X_i for all $i=1, \ldots, c$. This is known as clustering X into c clusters $X_1, \ldots, X_c$ using $\{\mu_1, \ldots, \mu_c\}$. A fuzzy extension allows $\mu_i(x)$ taking values in the interval [0, 1] such that $\sum_{i=1}^{c}\mu_i(x)=1$ for all x in X. In this case, $\{\mu_1, \ldots, \mu_c\}$ is called a fuzzy c-partition of X. Thus, the FCM objective function J_{FCM} is defined as (Bezdek, 1981)

$$J_{\mathrm{FCM}}(\mu,v)=\sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^{m}d^2(x_j,v_i), \tag{1}$$

where $\mu=\{\mu_1, \ldots, \mu_c\}$ is a fuzzy c-partition with $\mu_{ij}=\mu_i(x_j)$, the weighted exponent m is a fixed number greater than one establishing the degree of fuzziness, $v=\{v_1, \ldots, v_c\}$ is the c cluster centers, and $d^2(x_j,v_i)=||x_j-v_i||^2$ represents the Euclidean distance or its generalization such as the Mahalanobis distance. The FCM algorithm is an iteration through the necessary conditions for minimizing J_{FCM} with the following update equations:

$$v_i=\frac{\sum_{j=1}^{n}\mu_{ij}^{m}x_j}{\sum_{j=1}^{n}\mu_{ij}^{m}} \quad (i=1,\ldots,c) \tag{2}$$

and

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{d(x_j,v_i)}{d(x_j,v_k)}\right)^{2(m-1)}}. \tag{3}$$

At each iteration, QUOTE μ and v are updated using (2) and (3). The FCM algorithm iteratively optimizes $J_{\mathrm{FCM}}(\mu, v)$ until $|\mu(l+1)-\mu^{l}|\le\varepsilon$ is the number of iterations.

From (1), it is clear that the objective function of FCM does not take into account any spatial dependence among X and consider each image pixel as an individual point. Also, the membership function in (3) is determined by $d^2(x_j, v_i)$, which measures the similarity between the pixel intensity and the cluster center. The closer the intensity values to the cluster center the higher the value of the membership. Therefore, the membership function is highly sensitive to noise. If an MR image is affected by noise or other artifacts, the intensity of the pixels would change which results in an incorrect membership and improper segmentation.

There are several approaches to reduce sensitivity of FCM algorithm to noise. The most direct technique is low pass filtering of the image and then applying the FCM algorithm. However, low pass filtering may lead to loss of some important details. Different extensions of FCM algorithm have been proposed by researchers in order to solve sensitivity to noise. Dave clustered the noise into a separate cluster which is unique from signal clusters