Improvement of MRI Brain Image Segmentation Using Fuzzy Unsupervised Learning

Keyvan Saneipour 1 and Mojtaba Mohammadpoor 2, *

1 Department of Electrical Engineering, Islamic Azad University, Gonabad Branch, Gonabad, Iran
2 Department of Electrical and Computer Engineering, University of Gonabad, Gonabad, Iran
*Corresponding author: Department of Electrical and Computer Engineering, University of Gonabad, 9691957678, Hafez 16 Ave., Gonabad, Iran. Tel: +98-912507444, Email: mohammadpur@gonabad.ac.ir

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Abstract

Background: Magnetic resonance imaging (MRI) plays an important role in clinical diagnosis. The ability of fuzzy c-mean (FCM) algorithm in segmenting MR images has been proven. Some MR images are contaminated with noise. FCM performance is degraded in noisy images. Several efforts are done to overcome this weakness.

Objectives: The aim of this study was to propose a new method for MR image segmentation which is more resistant than other methods when noisy MR images are confronted.

Materials and Methods: In this study, simulated brain database prepared by BrainWeb was be used for analysis. First FCM and its improvements were analysed and their ability in segmenting noisy MR images were evaluated. Next, knowing that applying genetic algorithm on improver fuzzy c-mean (IFCM) could improve its performance, a new segmentation method was proposed by applying particle swarm optimization on IFCM.

Results: The proposed algorithm was applied on some intentionally noise-added MR images. Similarity between the segmented image and the original one was measured using Dice index. Other off-the-shelf algorithms were also tested in the same conditions. The indices were presented together. In order to compare the algorithms’ performances, the experiments were repeated using different noisy images.

Conclusion: The obtained results show that the proposed algorithms have better performance in segmenting noisy MR images than existing methods.

Keywords: MRI Images, Segmentation, Fuzzy

1. Background

Brain disease is one of the most common diseases that threatens human health and is one of the hottest researches in the medical community and profession. Medical imaging is an essential tool for diagnosis, understanding and treatment of various diseases, including cancer. A vast majority of medical studies and diagnoses are carried out using Magnetic resonance imaging (MRI), positron radiation tomography and computed tomography (CT) scan. MRI is an important experimental investigation technique used for screening abnormal changes in tissues and organs (1). Among the available medical images, MRI images are of higher quality, and unlike some other imaging techniques that use ionizing radiation, MRI makes use of strong electromagnetic waves or radio frequencies; therefore, this imaging technique is one of the most widely used methods in medical science (2).

Diagnosis of brain disease requires a high resolution brain MRI. MRI images have a multidimensional nature and can provide accurate information about the disease (2).

In MRI, by applying an external field (B₀), the atomic cores of the body tissues are placed along this magnetic field. At this time, if a radio frequency (RF pulse) is applied at a specific frequency and a particular angle to a patient, the energy level of spins in various tissues of the body will change. For this purpose, firstly, spins of the desired tissues, such as the brain or heart are placed under a strong magnetic force, so that all spins are aligned with the applied field. Then an external radio frequency with appropriate frequency is applied. Spins change their direction based on the RF radio frequency, and their energy level will change. In the absence of this radio frequency, the spins release energy. By making use of MRI, the signal of released
energy can be measured, and it can be employed to provide imaging of various body tissues (3, 4).

The received signal and signal damping time constant provide important information about the molecular structure of the body. The amplitude of the signal corresponds to the density of the hydrogen atom in one part of the body. The damping time constant $T_1$ weighted determines long relaxation time and the damping time constant $T_2$ weighted specifies the transverse relaxation time of the type of molecule to which the hydrogen atom is bonded. In MRI images, the brightness of each area in the image indicates the size of one of the mentioned parameters. This is evident because this method has the ability to differentiate in atomic level and is one of the most accurate imaging methods (3, 4). Figure 1 shows the imaging techniques.

2. Objectives

The main objective of this research is developing a precise segmentation algorithm for noisy MRI images. The main focus is on a fuzzy clustering method based on evolutionary processing, in order to accurately segment the magnetic resonance images contaminated by different levels of noise.

3. Materials and Methods

Use of intelligent algorithms to diagnose human disease based on medical imaging methods, namely computer-aided diagnosis (CADx) systems contributes significantly to the radiologists’ decision-making process. The purpose of these systems is to minimize the efforts needed to investigate the lesion, and to reduce the number of false positive factors along with the cost of treatment (5). Computer-aided detection (CAD) systems for analyzing MRI images exist in the literature (6, 7).

3.1. Image Segmentation Techniques

One of the intelligent methods in analyzing images is the use of segmentation algorithms, which can be considered as a suitable approach in diagnosing and analyzing brain images. Image segmentation is widely used in the processing of different image applications, including clinical applications and medical research. The goal is to split the image into different regions, depending on several criteria.

Medical image segmentation is carried out with the aim of extracting features, measuring different parts of the image, categorizing image pixels into anatomical regions such as bones, muscles and blood vessels, as well as categorizing pixels into pathologic regions such as cancer, tissue abnormalities and multiple sclerosis.

Several efforts have been performed to make FCM robust against noise. For example Arora and Pandey have mix FCM by a fuzzy support vector machine (SVM) in (9). They have used image spatial information for introducing a noise adaptive FCM algorithm for MRI images segmentation. Xiao and Tong (10) have also shown that combining FCM and SVM can produce good application presentation. On the other hand, Venu has evaluated using Gaussian ker-
nals for FCM algorithm (11) and Lan et al. have used Ker- 
neled FCM combining image filtering method for this pur-
pose (12).
Applying metaheuristic on FCM is another way for 
making a robust algorithm against noise. Jansi and Sub-
ashini have tested it (16). Ghassabeh et al. have used 
an improved version of FCM (IFCM) for overcoming FCM 
algorithm weakness by introducing two new parameters 
for considering pixel's neighborhood and location effect 
called $\lambda$ and $\zeta$ (1). Then, they tried to optimize IFCM using 
genetic algorithm.

3.2. The Proposed Method (PSO-IFCM)
In this paper, a new method for reducing FCM sensitiv-
ty to noise is proposed. In this way, first the IFCM algo-
rithm (1) is applied to MRI images. In the next step, PSO 
algorithm is used to optimize the parameters. Figure 2 
shows the flowchart of the proposed algorithm.
The MRI image or its intentionally noise-added version 
is used as the input of the algorithm. First, some pre-
processing methods as well as skull stripping are applied 
on it to prepare it for other steps. Original FCM algorithm 
is performed over it to initially segment it into its four clus-
ter. Absorb feature and absorb distance parameters and 
their related $\lambda$ and $\zeta$ coefficients are calculated. These coef-
ficients are fed into PSO algorithm to find their optimized 
values.
PSO proposed by Eberhart et al. (17), is an iteratively 
computational method for solving the optimization prob-
lem. Recently it has gained more attention and has been 
more used for several applications (18, 19).
In the PSO, each particle represents a solution to the 
problem and moves around a multi-dimensional search 
space at the initial velocity assigned to the particles. Dur-
ing the flight, each particle adapts its location to its ex-
perience and experience of its neighboring particles, and 
uses the best place it encounters with itself and its neigh-
bors, and then the particles move towards the best solu-
tion, which is the particle that is more fitted. The perfor-
ance of each particle is measured in terms of fitness func-
tion. This act is repeated so as to achieve convergence.
The membership functions and cluster centers of the 
previously performed FCM algorithm is updated using the 
optimized values of PSO step. Finally segmenting the MR 
image using updated FCM will generate the output of the 
algorithm.

3.3. Data Collection
Simulated brain database (SBD), as a realistic MRI data 
volume, is used for validation of different computer-aided 
and quantitative techniques in the analysis of medical 
images. In this paper, a simulated MRI image with the 
weight of $T1 (181 \times 217 \times 181)$, is taken from BrainWeb im-
age database (20, 21). In order to see the algorithms’ per-
formance, some Gaussian noise is added to it. Segments 90 
to 100 of brain images in the presence of different noises 
were selected for segmentation using the proposed algo-
rithms, and performance of algorithms in different noises 
and segments was investigated.

3.4. Segmentation Evaluation Methods
There are several indicators for evaluating the segmenta-
tion techniques and quality of algorithms. In this re-
search, a standard metric that was more accurate was used 
to measure the performance of the proposed algorithms.

Figure 1. Different types of imaging techniques (Flair, fluid-attenuated inversion recovery; PDW, proton-density-weighted)
4. Results

To measure the performance of the proposed method, T1W brain images were used. During the experiments, for comparing the proposed algorithms, standard FCM clustering algorithm, Gaussian kernel FCM, and genetic algorithm improver fuzzy c-mean (GA-IFCM) were performed also. Following this, the results of each of the optimized and improved FCM clustering algorithms were compared.

Figure 3A is the 90th segment of the simulated MR image with the weight of T1, and Figure 3B illustrates the image in the presence of 5% noise, and the segmentation operation is shown in Figure 3C, which is the result of applying the proposed PSO-IFCM algorithm. Each brain MR image can have four clusters namely, background (BGND), gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) (1). Every algorithm that extracts these tissues by higher precision has a better performance. To evaluate the accuracy of segmentation, Dice coefficient (DC) described in equation 1 is used. The results of this section are illustrated in Table 1.

In order to see the performance of the proposed algorithm in noisy images, all algorithms were applied over MR images contaminated by different levels of noise. Figure 4 shows a continuous chart of Dice coefficient for different noises at 100th cut of brain MR image.

5. Discussion

The advantage of basic FCM clustering algorithm in segmenting MR images is shown the literature. As shown in Table 1, FCM and all its derivations, including PSO-IFCM as the proposed method, have acceptable segmental accuracy in low noise images. All the algorithms have above 97% accuracy in segmenting this image. Figure 3 shows the algorithm performances in noisy images. The horizontal axis is percentage of Gaussian noise added to 100th cut MR image. The vertical axis shows the DC value of segmentation. As shown, with the increase of noise, the accuracy of basic FCM and kernel FCM (KFCM) algorithms drops. But enhanced FCM algorithms such as GA-IFCM and PSO-IFCM are more robust against noise augmentation. In high noises, GA-IFCM and PSO-IFCM algorithms function similarly, and the accuracy of these algorithms is very close to each other.

In conclusion, according to the importance of analyzing magnetic resonance images of the brain, a new seg-
A 

Figure 3. An example of the implementing the proposed algorithm

| Brain tissues | Metric, % | FCM     | KFCM    | GA-IFCM | PSO-IFCM |
|---------------|-----------|---------|---------|---------|----------|
| WM            | DC        | 98.1745 | 98.1745 | 98.605  | 98.6099  |
| GM            | DC        | 96.0919 | 97.0543 | 97.821  | 97.8232  |
| CSF           | DC        | 97.3572 | 98.6455 | 99.332  | 99.1318  |
| BGND          | DC        | 99.4399 | 99.7556 | 99.916  | 99.9185  |
| Average       | DC        | 97.7659 | 98.4075 | 98.868  | 98.8708  |

Abbreviations: BGND, background; CSF, cerebrospinal fluid; DC, Dice coefficient; FCM, fuzzy c-means; GA-IFCM, genetic algorithm-improver fuzzy c-mean; GM, gray matter; KFCM, kernel FCM; PSO-IFCM, particle swarm optimization-improver fuzzy c-mean; WM, white matter

Figure 4. Continuous chart of DC for different noises at 100th cut from brain MR image (DC, Dice coefficient; FCM, fuzzy c-means; GA-IFCM, genetic algorithm-improver fuzzy c-mean; KFCM, kernel FCM; PSO-IFCM, particle swarm optimization-improver fuzzy c-mean)

in the presence of different levels of noise, the advantages over the existing methods is shown. Fuzzy clustering method has a higher accuracy and processing speed than classical methods. The results of applying standard FCM algorithm on noisy brain MRI imagery indicate that is has a desirable accuracy for very low noise. For moderate noise, the KFCM algorithm has a desirable accuracy. For high noise, the GA-IFCM and PSO-IFCM algorithms are well-suited. Main limitation of using metaheuristic algorithms such as GA and PSO is their consumed time. As the segmentation methods are used offline, no processing time comparison between algorithms is done in this paper.

Footnotes

Authors’ Contributions: This paper was extracted from Keyvan Saneipour Master thesis with the same name in Department of Electrical Engineering, Islamic Azad University, Gonabad Branch under supervision of Mojtaba Mohammadpoor. The original idea and method was proposed by Mojtaba Mohammadpoor. Keyvan Saneipour prepared the thesis, collected the data and applied and tested the
method. After the viva, the paper was extracted and prepared by Mojtaba Mohammadpoor.

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