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A Swarm-based Approach to Medical Image Analysis

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Received: 8 January 2011 Accepted: 1 February 2011 Published: 15 February 2011

Abstract

Image segmentation is an indispensable part of the visualization of human tissues, particularly during analysis of Magnetic Resonance (MR) images. Unfortunately images always contain a significant amount of noise due to operator performance, equipment, and the environment can lead to serious inaccuracies with segmentation. A segmentation technique based on an extension to the traditional C-means (FCM) clustering algorithm is proposed in this paper. A neighborhood attraction, which is dependent on the relative location and features of neighboring pixels considered.. The degree of attraction is optimized by a Particle Swarm Optimization model. Paper demonstrates the superiority of the proposed technique to FCM-based method. This segmentation method is component of an MR image-based classification system for tumors, currently being developed.

Index terms—

1 INTRODUCTION

n the analysis of medical images for computer-aided diagnosis and therapy, segmentations is often required as a preliminary stage. Medical image segmentation is a complex and challenging task due to the intrinsic nature of the images. The brain has a particularly complicated structure and its precise segmentation is very important for detecting prescribe appropriate therapy. Magnetic resonance imaging (MRI) is an important diagnostic imaging technique for the early detection of abnormal changes in tissues and organs. It possesses good contrast resolution for different tissues and has advantages over computerized tomography (CT) for brain studies due to its superior contrast properties. Therefore, the majority of research in medical image segmentation concerns MR images.

Many image processing techniques have been proposed for brain MRI segmentation, most notably thresholding, region-growing, and clustering. Since the distribution of tissue intensities in brain images is very complex, it leads to difficulties of threshold determination.

Therefore, thresholding methods are generally restrictive and have to be combined with other methods [1], [2]. Region growing extends thresholding by combining it with connectivity conditions or region homeogeneity criteria. Successful methods require precise anatomical information to locate single or multiple seed pixels for each region and together with their associated homogeneity [3]- [5], Clustering is the most popular method for medical image segmentation, with fuzzy c-means (FCM) clustering and expectationmaximization (EM) algorithms being the typical methods. The applications of the EM algorithm to brain MR image segmentation were reported by Wells et al. [6] and Leemput et al. [7]. A common disadvantage of EM algorithms is that the intensity distribution of brain images is modeled as a normal distribution, which is untrue, especially for noisy images.

The FCM algoirthm has also been employed by many researchers. Li et al. [8] presented a knowledgebased classification and tissue labeling approach to initially segment MR brain images using the FCM algorithm FCM was shown to be superior on normal brains, but worse on abnormal brains with edema, tumor, etc. Pham and Prince [10] extended the traditional FCM algorithm to deal with MR images corrupted by intensity inhomogeneities. Unfortunately, the greatest shortcoming of FCM is its over-sensitivity to noise, which is also a flaw of many other intensity-based segmentation methods. Since medical images always include considerable uncertainty and unknown noise, this generally leads to further degradation with segmentation.

An MR image-based brain tumor classification system is being developed by the authors, and this was the initial motivation to develop a robust segmentation method, since accurate and robust segmentation is a key stage in successful classification. Many extensions of the FCM algorithm have been reported in the literature to overcome the effects of noise, but most of them still have major drawbacks. In this paper, new extensions to FCM are described which consider two influential factors in segmentation, both of which address issues of neighborhood attraction. One is the feature difference between neighboring pixels in the image; the other is the relative locations of neighboring pixels. Segmentation is therefore decided not only by the pixel intensities themselves, but also by the neighboring pixel intensities and locations. Consideration of these neighboring pixels greatly restrains the influence of noise. The parameters referring to the degree of neighborhood attraction are determined using a simple PSO model.

2 1) IFCM Algorithm

To overcome the drawbacks of FCM, Shen et al. presented an improved algorithm. They found that the similarity function d2 **??**xj, vi) is the key to segmentation success. In their approach, an attraction entitled neighborhood attraction is considered to exist between neighboring pixels. During clustering, each pixel attempts to attract its neighboring pixels towards its own cluster. This neighborhood attraction depends on two factors; the pixel intensities or feature attraction ?, and the spatial position of the neighbors or distance attraction ?, which also depends on the neighborhood structure. Considering this neighborhood attraction, they defined the similarity function as below:( ) ( ) ij ij i j i j F H v x v x d ? ? ? ? ? ? = 1 , 2 2

where Hij represents the feature attraction and Fij represents the distance attraction. Magnitudes of two parameters ? and ? are between 0 and 1; adjust the degree of the two neighborhood attractions. Hij and Fij are computed in a neighborhood containing S pixels as follow:? ? s jk k s jkgjk k ij H µ µ 1 1 ? ? s k s q k ij ik jk ik F 2 2 2 1 1 µ µ With ( ) ( ) 2 2 , k j k j jk k j b b a a q x x gjk ? + ? = ? =

where (aj,bj) and (ak,bk) denote the coordinate of pixel j and k, respectively. It should be noted that a higher value of ? leads to stronger feature attraction and a higher value of ? leads to stronger distance attraction. Optimized values of these parameters enable the best segmentation results to be achieved. However, inappropriate values can be detrimental. Therefore, parameter optimization is an important issue in IFCM algorithm that can significantly affect the segmentation results.

2) Parameter Optimization Of IFCM Algorithm Optimization algorithms are search methods, where the goal is to find a solution to an optimization problem, such that a given quantity is optimized, possibly subject to a set of constrains. Although this definition is simple, it hides a number of complex issues. For example, the solution may consist of a combination of different data types, nonlinear constrains may restrict the search area, the search space can be convoluted with many candidate solutions, the characteristics of the problem may change over time, or the quantity being optimized may have conflicting objectives As mentioned earlier, the problem of determining optimum attraction parameters constitutes an important part of implementing the IFCM algorithm. Shen et al. (**??**005) computed these two parameters using an ANN through an optimization problem. However, designing the neural network architecture and setting its parameters are always complicated tasks which slow down the algorithm and may lead to inappropriate attraction parameters and consequently degrade the partitioning performance. In this paper, a new computational method based on particle swarm optimisation introduced in order to compute optimum values of these two parameters.

3 3) Structure of Particle Swarm Algorithm

The PSO conducts searches using a population of particles which correspond to individuals in GAs. The population of particles is randomly generated initially. Each particle represents a potential solution and has a position represented by a position vector &xi. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a position vector &vi. At each time step, a function fi representing a quality measure is calculated by using &xi as input. Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector & pi. Furthermore, the best position among all the particles obtained so far in the population is kept track of as &pg. At each time step ? , by using the individual best position, &pi(?), and global best position, &pg(?), a new velocity for particle i is updated by Where c1 and c2 are acceleration constants and ?1 and ?2 are uniformly distributed random numbers in [0, 1]. The term &vi is limited to its bounds. If the velocity violates this limit, it is set to its proper limit. w is the inertia weight factor and in general, it is set according to the following equation:? . min max max T w w w w ? ? = ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ? ? ? ? ? ? ? ? ? ? i g i i i i x p C x p c w ? + ? + = + 2 2 1 1 ( ) ( ) ( ) ()1 1 + + = + ? ? ? ? i i i v h x x March 2011 = = = = = = ©2011 Global Journals Inc. (US)

Where h max and h0 are positive constants.

The population of particles tend to cluster together with each particle moving in a random direction. The computation of PSO is easy and adds only a slight computation load when it is incorporated into IGA. Furthermore, the flexibility of PSO to control the balance between local and global exploration of the problem space helps to overcome premature convergence of elite strategy in GAs, and also enhances searching ability. The global best individual is shared by the two algorithms, which means the global best individual can be achieved by the GA or by PSO, also it can avoid the premature convergence in PSO.

After completion of above processes, a new population is produced and the current iteration is completed. We iterated the above procedures until a certain criterion is met. At this point, the most fitted particle represented the optimum values ? and ?. Simulations are done on one sample Tl weighted MR image. In first experiment, noise is absent and in second and third experiments, noise is present and effect of noise increases. In each experiment, parameters ? and ? are computed using proposed optimization method based on PSO algorithm. Then we used IFCM clustering algorithm in order to segment MR images. Figure **??** shows a noiseless MR image and segmented images, from left to right they are, original image, white matter, gray matter and CSF.

4 II. simulation results

5 Table1

In the second experiment, Tl weighted MR image destroyed with Gaussian noise. Figure **??** demonstrates the results of segmentation. In third experiment, we increased amount of Gaussian noise and corrupted the original image. Figure **??** shows results of segmentation in this case.

6 III. conclusion

There are different sources of noise, arising from environment, operator, and equipments. These sources influence the medical images. As a result, performance of traditional FCM for segmentation of noisy images reduces. IFCM algorithm is proposed to solve sensitivity of FCM algorithm to noise. This version of FCM introduces two new parameters X and in order to consider pixel's neighborhood and location effect. The new parameters are computed using an ANN through optimization of an objective function. In this paper a new method based on PSOs is introduced for computation of the optimal values of these parameters. Simplified computation of X and (, is an Advantage of the proposed algorithm compared with ANN optimization technique. Simulation results demonstrated effectiveness of the new proposed method to find optimal values of X and (, that are used for efficient segmentation of noisy MR images.

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Where ( ) ( )T h h h h o ? ? . max max ? ? =

Where wmax and wmin is maximum and minimum value of the weighting factor respectively. T is the maximum number of iterations and ? is the current iteration number. Based on the updated velocities, each particle changes its position according to the following:

Figure 1:

Experimental results demonstrate improved performance of FCM clustering algorithm against noisy MR images. New proposed algorithm based on PSO, simplifies computation of ? and ? without using complicated ANN.

Figure 2:

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[A Swarm-based Approach to Medical Image Analysis Global Journal of Computer Science and Technology Volume XI Issue III V *A Swarm-based Approach to Medical Image Analysis Global Journal of Computer Science and Technology Volume XI Issue III Version I*, 26 March 2011.

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