**A Hybrid Technique for Medical Image Segmentation**

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2. Proposed Image Segmentation Framework

The proposed image segmentation approach consists of vector median filtering, which is used to reduce impulsive noise in medical images, Otsu thresholding, which is then employed for rough segmentation of brain MR images, and EnSFCM, which is applied to have well-segmented images. More details about the proposed approach are described in Figure 1 and the following sections.

2.1. Vector Median Filter

In medical images, impulsive noise, which is randomly distributed over the image, is independent and uncorrelated to the image pixels. In magnetic resonance (MR) images, the low resolution of sensors is the cause of impulsive noise in the partial volume [11, 15], which can result in low segmentation performance. Thus this paper uses a vector median filter (VMF) to remove that impulsive noise. VMF can be used because it preserves the image without getting blurred and no shifting of boundary [16]. Its approach is the searching the most robust vector in the processing window. This process is as follows.

Assume that I is an image to be processed, and W is the processing window centered on the pixel under processing of size N×N, N=3, 5, 7,.... and so forth. We consider that each input vector xi is associated with the distance measure,

for *i =* 1,2,...,*N,* (1)

where *γ* represents the selected norm. The distance between two samples can be defined by

, (2)

where *m* is the distance of the vectors and *xik* is the *k*th element of *xi*. Thus distance *Li* serves as an ordering criterion of which implies the same ordering of the input vectors. The VMF output of the set is defined as the sample that satisfies the following condition:

, for *j* = 1,2,…,*N*. (3)

2.2. Otsu Thresholding

Otsu’s algorithm is one of the most referenced thresholding methods in image segmentation. It automatically selects threshold values from the histogram of the image by using the variance property of the image. The variance property is used because the greater difference between variance values represents the greater difference between the background and the object [4, 6]. Initially, two regions are separated by the intensity threshold, and then minimizing the within-class variance or maximizing the between-class variance determines the optimal threshold.

Assume that are the probabilities of the gray-level image histogram of an image, where *L* is the range of intensity levels. We can calculate the probabilities of background () and the probabilities of object () of the image with a threshold *t* as follows:

, (4)

,

The mean associated with the background and the object can be further calculated using the following equations:

, (5)

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We can compute variance by using mean values as follow:

, (6)

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The between-class variance which is the weighted variance of the cluster means around the overall mean is defined as follows:

, (7)

where is the global mean of the image. Furthermore, the within-class variance can be expressed as follows:

(8)

Finally, the optimal threshold value,, can be determined by maximizing the between-class variance or equivalently minimizing the with-class variance as follows:

, (9)

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2.3. Enhanced Suppressed Fuzzy C-Means

Fuzzy c-means (FCM) is one of the data clustering techniques playing an outstanding role in image segmentation, feature extraction, and pattern recognition [9, 17]. Based on the membership value, FCM can split a data into several different groups. However, it sometimes leads to accuracy degradation with the conventional FCM, so suppressed FCM (SFCM) has been proposed to improve the clustering performance and the speed of convergence. SFCM algorithm proposes the suppression factors for establishing a relationship between hard c-means (HCM) and FCM clustering algorithm [10]. Furthermore, to optimize in any sense as well as conform for any given purpose, we propose an enhanced suppressed FCM (EnSFCM) to automatically select the suppression factor for SFCM. The selection method of the suppression factor, α, is based on the separation strength between clusters that is a time variant suppression rate. More details about EnSFCM are as follows.

Let where is the number of image pixels. The conventional FCM algorithm sorts the data set into clusters. The standard FCM objective function is defined as follows:

, (10)

where is the Euclidian distance between the data point and the centroid of the ith cluster and is the degree of membership of the data to the cluster. The parameter is called the fuzzy factor controls the fuzziness of the resulting partition and c is the total number of clusters. FCM clustering is a clustering technique based on iteration in which an optimal number of c classes are produced by minimizing the objective function with updated values of and according to the following equations:

, (11)

.

SFCM modifies the membership function in FCM by utilizing the suppression factor as follows:

, (12)

,

where refers to data point, belongs to the largest cluster ,and is the suppression factor which ranges in the interval [0, 1]. When termination measurement is satisfied, where are the current centroids, are the previous centroids, for, and is a predefined termination threshold, the pixel clustering iterations are terminated. As mentioned before, it is necessary to choose an optimal suppression factor for SFCM so we define a new exponential function, and it is automatically updated at each iteration:

, (13)

where is the centroid of the ith cluster, is the centroid of the cluster, and is the degree of fuzzification. Higher values ​​of the suppression factor α indicate that FCM is superior to HCM whereas lower values ​​represent the opposite. As you can see we get the better clustering performance with compact clusters by giving more distance between centroids. Similarly, both the fuzzification parameter and the suppression rate α affect the learning rate of the algorithms. The fuzzy factor represents the fuzziness of the membership values ​​for the clustered data points.