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Segmentation techniques for tissue differentiation in MRI of Ophthalmology using fuzzy clustering algorithms

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Abstract

This paper presents MRI segmentation techniques to differentiate abnormal and normal tissues in Ophthalmology using fuzzy clustering algorithms. Applying the best-known fuzzy *c*-means (FCM) clustering algorithm, a newly proposed algorithm, called an alternative fuzzy *c*-mean (AFCM), was used for MRI segmentation in Ophthalmology. These unsupervised segmentation algorithms can help Ophthalmologists to reduce the medical imaging noise effects originating from low resolution sensors and/or the structures that move during the data acquisition. They may be particularly helpful in the clinical oncological field as an aid to the diagnosis of Retinoblastoma, an inborn oncological disease in which symptoms usually show in early childhood. For the purpose of early treatment with radiotherapy and surgery, the newly proposed AFCM is preferred to provide more information for medical images used by Ophthalmologists. Comparisons between FCM and AFCM segmentations are made. Both fuzzy clustering segmentation techniques provide useful information and good results. However, the AFCM method has better detection of abnormal tissues than FCM according to a window selection. Overall, the newly proposed AFCM segmentation technique is recommended in MRI segmentation. © 2002 Elsevier Science Inc. All rights reserved.

Keywords: Image segmentation; Magnetic resonance image (MRI); Fuzzy *c*-means algorithm; Alternative fuzzy *c*-means algorithm

1. Introduction

In clinical diagnosis, the segmentation of medical images is an important step. The clustering segmentation can be successfully used in the discrimination of different tissues from the medical images (see [1]). However, most medical images always present overlapping gray-scale intensities for different tissues. MRI medical imaging uncertainty is widely presented in data because of the noise and blur in acquisition and the partial volume effects originating from the low resolution of the sensors. In particular, borders between tissues are not clearly defined and memberships in the boundary regions are intrinsically fuzzy. The conventional (hard) clustering methods restrict each point of the data set to exactly one cluster. Fuzzy sets give the idea of uncertainty of belonging described by a membership function. Therefore, fuzzy clustering methods turn out to be particularly suitable for the segmentation of MRI medical images. In this paper we focus our attention on the fuzzy *c*-mean (FCM) and alternative fuzzy *c*-mean (AFCM) methods and the resolution of MRI segmentation uncertainty in Ophthalmology cases.

An efficient analysis of dual echo medical imaging volumes can be derived from a set of such different diagnostic volumes carrying complementary information (e.g. both structural and functional) provided by medical imaging technology. The extraction of such volumes from imaging data is called segmentation and it is usually performed, in the image space, defining sets of vowels with similar features within a whole dual echo volume. The segmentation can be described as the definition of clusters whose points are associated to similar sets of intensity values in the different images. Moreover, problems in improving the visual quality of these digital images were related to the selection of printing procedures and the distribution of brightness levels. For blurred pictures, image enhancement and restoration procedures are used to process the degraded

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images of unrecoverable objects or experimental results too expensive to duplicate. In general, medical images are obtained by different acquisition modalities, including X-ray tomography (CT), single photon emission tomography (SPECT), positron emission tomography (PET), ultrasound (US), magnetic resonance image (MRI) and MR angiographies (MRA), etc. The MRI systems are important in medical image analysis. In clinical diagnosis, these MRI systems have been successfully used in detecting various abnormal tissues. Image segmentation is an important step in any image analysis system. A variety of segmentation techniques for MRI have been studied and reported [2–4].

Cluster analysis is a tool for clustering a data set into groups of similar individuals. Image segmentation is a method to partition image pixels into similar regions. Thus, clustering algorithms would naturally be applied to enhance images in using segmentation areas. The conventional (hard) clustering methods restrict each point of the data set to exactly one cluster. Since Zadeh [5] proposed fuzzy sets which produced the idea of overlapping membership in two or more sets described by a membership function, fuzzy clustering has been widely studied and applied in various areas [6,7]. In the fuzzy clustering literature, the FCM clustering algorithm is the most used method. Recently, this FCM algorithm has been more frequently used in segmenting MRI. However, most FCM segmentation techniques are usually used in segmenting brain MRIs [8–10]. In this paper, we pay particular attention to the MRI segmentation in Ophthalmology.

In the oncological field, physicians depend on different clinical frameworks, different anatomical evidences and different theoretical approaches, etc. to diagnose a patient. It is often impossible to establish rule-based systems [11]. MRI or computer-assisted approaches may be particularly helpful in the clinical oncological field as support in the diagnosis of Retinoblastoma, an inborn oncological disease in Ophthalmology, which usually shows its symptoms in early childhood. For the purpose of early treatment with radiotherapy and surgery, the FCM clustering algorithm was introduced to the diagnosis of every Retinoblastoma patient. Recently, Wu and Yang [12] proposed a new algorithm called alternative fuzzy c-means (AFCM) which provides more information available in medical images. In this paper we use FCM and AFCM segmentation techniques for tissue differentiation in Ophthalmological MRIs. We present a case study of Retinoblastoma patients who were diagnosed using MRI in the Ophthalmology field. Both FCM and AFCM segmentation techniques provide useful information and good results. However, the AFCM has better detection of abnormal tissues than FCM based on a window selection. Section 2 presents materials and methods. Results of the case study are presented in Section 3. Conclusions are presented in Section 4.

2. Materials and methods

2.1. Case summary

The used MRI data sets in this paper are from the patient of a 2 year old girl. She was diagnosed with Retinoblastoma of her left eye, an inborn malignant neoplasm of the retina with frequent metastasis beyond the lacrimal cribrosa. The CT scan image showed a large tumor with calcification occupying the vitreous cavity of the left eye. Therefore, she was admitted to receive an MRI scan and consultation with an oncology specialist. Two MR images were acquitted. The MR images showed that an intra muscle cone tumor mass with high T1-weight signal images and low signals on T2-weight images are noted in the left eyeball. The tumor measured 20 mm in diameter and nearly occupied the entire vitreous cavity. There was a shady signal abnormality along the optic nerve to the level of the optic chiasma toward the brain. MR image obtained by a 1.5 T MR scanner with a multi-element resonator head coil. They were acquitted in the transaxial plane using a multisided interleaved two-dimensional (2D) Fourier transform technique, with a field of view (FOV) $= 16 \times 16$ mm, slice thickness $= 3.0$ mm, Gap $= 5$ mm, and a 256×256 pixel matrix, that is, contiguous slices were acquitted. A standard spin-echo (SE) sequence with TR $= 300$ ms with TE $= 13$ for the first picture and TR $= 583$ ms and TE $= 17$ for the second picture to produce MR images.

From the first MRI data set (Figs. 1–6) there is a shady signal abnormality along the optic nerve to the level of optic chiasma. From the second MRI data set (Fig. 7) one lesion was clearly seen by MR image and few fuzzy shadow of lesions were suspected with tumor invasion. Unsupervised fuzzy clustering algorithms would be used to analyze these MRI data sets and should be introduced to Retinoblastoma patient as a support method to diagnosis. The segmentation results will be shown in Section 3.

2.2. Fuzzy clustering segmentation

The segmentation of imaging data involves partitioning the image space into different cluster regions with similar intensity image values. The most medical images always present overlapping gray-scale intensities for different tissues. Therefore, fuzzy clustering methods are particularly suitable for the segmentation of medical images. There are several FCM clustering applications in the MRI segmentation of the brain, but less report on MRI segmentation in Ophthalmology. The application of fuzzy clustering to MRI segmentation in Ophthalmology will be our main topic. We used FCM and AFCM clustering algorithms to segment Ophthalmological MRIs.

Let $X = \{x_1, \cdots, x_n\}$ be a data set. Let c be a positive integer greater than one. A partition of X into c clusters can be presented by mutually disjoint sets $X_1, \cdots, X_c$ such that $X_1 \cup \cdots \cup X_c = X$ or equivalently by the indicator functions $\mu_1, \cdots, \mu_c$ 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 $i = 1, \cdots, c$. This is known as clustering X into c clusters $X_1, \cdots, X_c$ by a so-called hard c-partition $\{\mu_1, \cdots, \mu_c\}$. The well-known k-mean (or called hard c-mean) is an iteration algorithm to minimize the objective function J_{HCM} defined as

$$J_{HCM}(\mu, a) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_i(x_j)\|x_j - a_i\|^2$$

where $a_1, \cdots, a_c$ are the c cluster centers.

The fuzzy extension allows $\mu_i(x)$ to be membership functions in fuzzy sets μ_i on X assuming values in the interval [0, 1] such that $\sum_{i=1}^{c} \mu_i(x) = 1$ for all x in X. In this case, $\{\mu_1, \cdots, \mu_c\}$ is called a fuzzy c-partition of X. Thus, the fuzzy c-mean (FCM) objective function J_{FCM} becomes

$$J_{FCM}(\mu, a) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_i^m(x_j)\|x_j - a_i\|^2$$

where $\{\mu_1, \cdots, \mu_c\}$ is a fuzzy c-partition and m is a fixed number bigger than one to present the degree of fuzziness. The FCM clustering algorithm is an iteration through the necessary conditions for minimizing J_{FCM} with the following update equations [6,7]:

$$a_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m}, \ i = 1, \cdots, c \qquad (1)$$

and

$$\mu_{ij} = \mu_i(x_j) = \left(\sum_{k=1}^{c} \frac{\|x_j - a_i\|^{2/(m-1)}}{\|x_j - a_k\|^{2/(m-1)}} \right)^{-1}, \ i = 1, \cdots, c, \quad j = 1, \cdots, n. \qquad (2)$$

Thus the FCM clustering algorithm is presented as follows:

<u>FCM algorithm</u>

S1: Fix $m > 1$ and $2 \le c \le n$ and set $k = 1$. Give any $\epsilon > 0$ and an initial fuzzy c-partition $\mu^{(0)} = \{\mu_1^{(0)}, \cdots, \mu_c^{(0)}\}$.

S2: Compute $a^{(k)}$ with $\mu^{(k-1)}$ by equation (1).

S3: Update $\mu^{(k)}$ with $a^{(k)}$ by equation (2).

S4: Compare $\mu^{(k)}$ to $\mu^{(k-1)}$ in a convenient norm $\|\mu^{(k)} - \mu^{(k-1)}\|$.

IF $\|\mu^{(k)} - \mu^{(k-1)}\| < \epsilon$, THEN stop

ELSE $k = k + 1$ and return to S2.

The FCM clustering algorithm has been widely used and applied in MRI segmentation. However, this FCM algorithm has considerable trouble with noisy or outlying points. It is also inaccurate with clusters of different volume and unequal sample sizes. In order to have a clustering algorithm with more robustness and the ability to tolerate these situations, Wu and Yang [12] proposed a new distance function defined as

$$d^2(x, y) = 1 - \exp(-\beta\|x - y\|^2)$$

to replace the Euclidean metric $d^2(x, y) = \|x - y\|^2$. They then considered a so-called alternative fuzzy c-means (AFCM) objective function as

$$J_{AFCM}(\mu, a) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_i^m(x_j)(1 - \exp(-\beta\|x_j - a_i\|^2))$$

where $m > 1$ and $\beta > 0$ and $\{\mu_1, \cdots, \mu_c\}$ is a fuzzy c-partition. The Picard's iteration for minimizing J_{AFCM} are the following update equations:

$$a_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m \exp(-\beta\|x_j - a_i\|^2)\, x_j}{\sum_{j=1}^{n} \mu_{ij}^m \exp(-\beta\|x_j - a_i\|^2)}, i = 1, \cdots, c \qquad (3)$$

and

$$\mu_{ij} = \mu_i(x_j) = \left(\sum_{k=1}^{c} \frac{(1 - \exp(-\beta\|x_j - a_i\|^2))^{1/(m-1)}}{(1-\exp(-\beta\|x_j - a_k\|^2))^{1(m-1)}} \right)^{-1}, \quad i = 1, \cdots, c, j = 1, \cdots, n \qquad (4)$$

where the parameter β can be estimated by the inverse of the sample variance with

$$\beta = \left(\sum_{j=1}^{n} \|x_j - \bar{x}\|^2/n\right)^{-1}, \bar{x} = \sum_{j=1}^{n} x_j/n. \qquad (5)$$

Thus the AFCM clustering algorithm can be described as follows:

<u>AFCM algorithm</u>

S1: Fix $m > 1$ and $2 \le c \le n$. Set $k = 1$. Give any fixed $\epsilon > 0$ and an initial fuzzy c-partition $\mu^{(0)} = \{\mu_1^{(0)}, \cdots, \mu_c^{(0)}\}$.

S2: Estimate parameter β using equation (5).

S3: Compute $a^{(k)}$ with $\mu^{(k-1)}$ using equation (3).

S4: Update $\mu^{(k)}$ with $a^{(k)}$ using equation (4).

S5: Compare $\mu^{(k)}$ to $\mu^{(k-1)}$ is a convenient norm $\|\mu^{(k)} - \mu^{(k-1)}\|$.

IF $\|\mu^{(k)} - \mu^{(k-1)}\| < \epsilon$, THEN stop

ELSE $k = k + 1$ and return to S3.

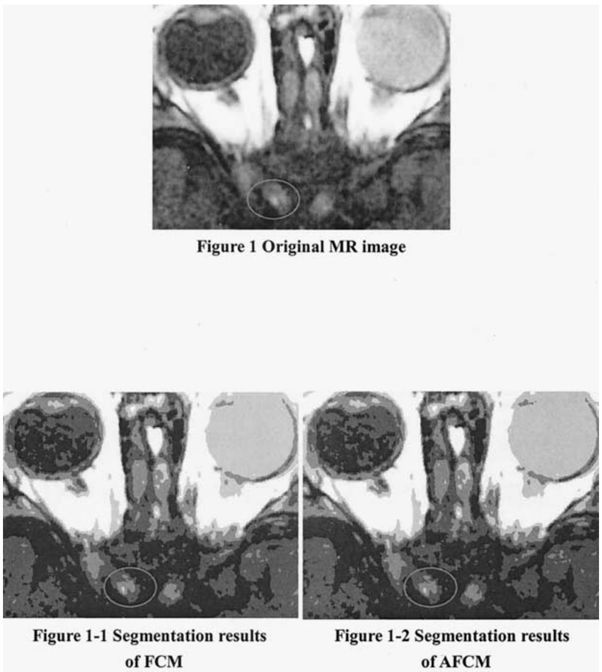

Figure 1 Original MR image

Figure 1-1 Segmentation results of FCM

Figure 1-2 Segmentation results of AFCM

Fig. 1.

Wu and Yang [12] presented more AFCM properties. Comparisons between AFCM and FCM were made. They showed that the AFCM is more robust to outliers and tolerates clusters of different volume better than the FCM. In this paper we applied FCM and AFCM in MRI segmentation in Ophthalmology. The results and comparisons will be shown in the next section.

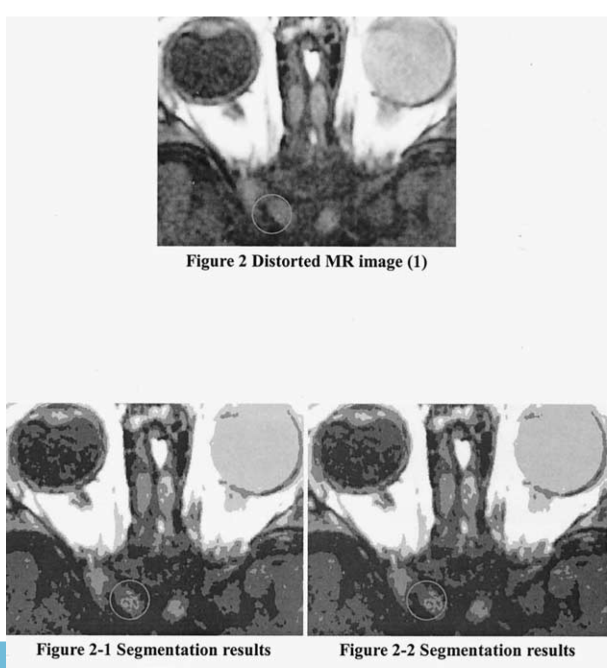

Figure 2 Distorted MR image (1)

Figure 2-1 Segmentation results of FCM

Figure 2-2 Segmentation results of AFCM

Fig. 2.

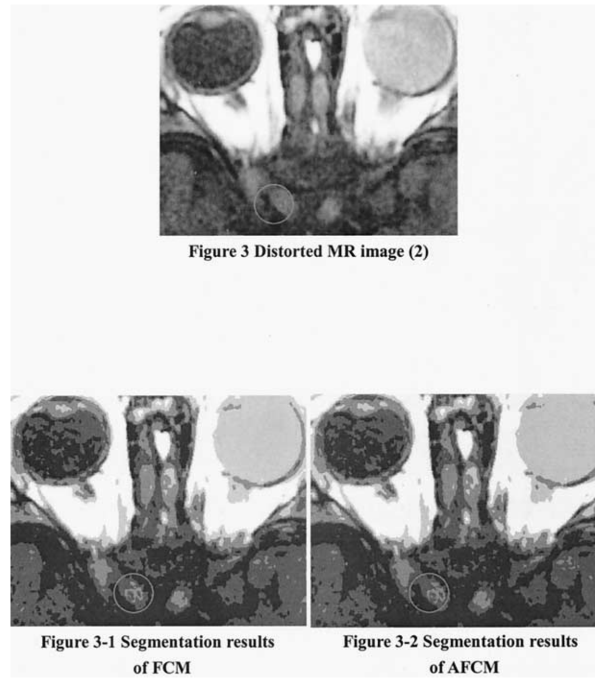

Figure 3 Distorted MR image (2)

Figure 3-1 Segmentation results of FCM

Figure 3-2 Segmentation results of AFCM

Fig. 3.

3. Results

The FCM and AFCM clustering algorithms are used to determine the actual symptoms of Retinoblastoma from MRI and determine if further treatment is necessary. Since glioblastoma is hereditary, children whose families have a history of this problem can undergo periodic diagnostic tests with MRI using the FCM and AFCM algorithms to detect

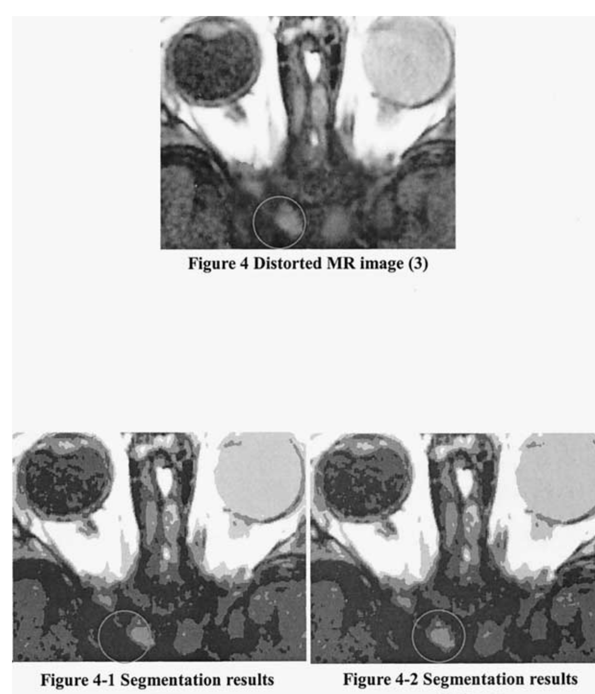

Figure 4 Distorted MR image (3)

Figure 4-1 Segmentation results of FCM

Figure 4-2 Segmentation results of AFCM

Fig. 4.

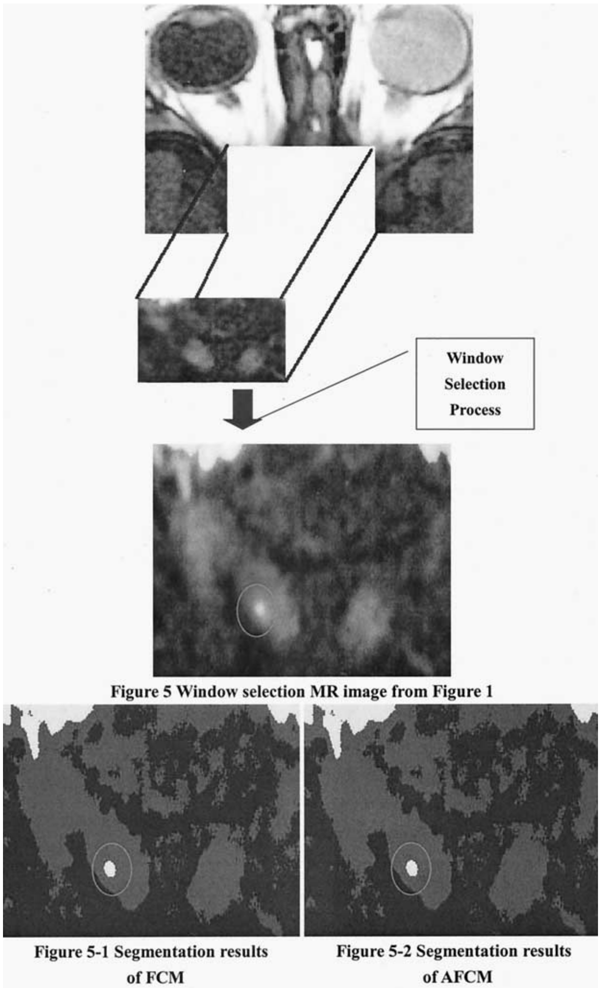

Fig. 5.

the smallest sign symptoms for early detection and treatment.

From experiments we determined that applying the clustering algorithms to the full size image with a large number of pixels results in excessively long processing time. High sensor resolution and coil position are essential because the size of the tumor can be as small as 0.01 mm^3. MRI has limitations in detecting small tumors. Therefore, we would use window segmentation to enhance parts of the tumor for closer determination.

Here we analyzed two MRI data sets. The first MRI data set includes in Figs. 1–6. The second MRI data set includes in Fig. 7. We first attempted to group the full size images (Figs. 1–4) into five clusters that were recommended by an Ophthalmologist. The categories are as follows: Muscle tissue, connective tissue, nervous tissue, the lens, and tumor tissue. After image segregation and reading the gray scale histogram, we discovered that there were five picks that appeared in the full-size image. In order to detect small tumors, we then used window segmentation (Figs. 5–6 for the first MRI data set and Fig. 7 for the second MRI data set) to enhance parts of the tumor under the recommendations of

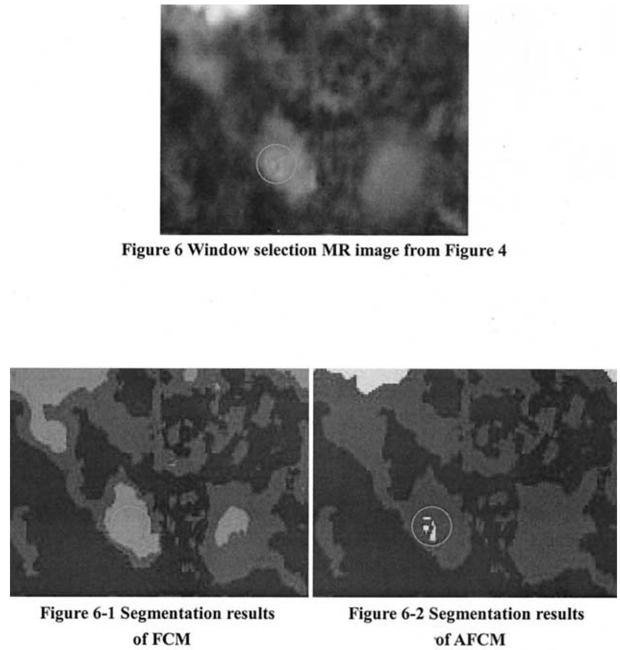

Fig. 6.

specialists. The lens and muscle tissue were excluded from the window, so the original five categories were decreased to three: connective tissue, nervous tissue and tumor tissue. A gray scale histogram comparison proves that there are actually three picks that appear in the segmentation window image. The histogram picks for the gray scale provided us with a set of best starting points for the clustering algorithms.

The four pictures (Figs. 1–4) were processed at 400 $\times$ 286 pixels. The pictures are clustered into four tissue classes and one tumor class. The two window selection pictures from the first MRI data set (Figs. 5 and 6) were processed at 296 $\times$ 161 pixels. The pictures accommodate reduced image tissue movement contrast and the axial extremes of the transmission and receiving coils. The pictures are grouped into three tissue types: Connective tissue, nervous tissue and tumor tissue. From the red circle on the full size two dimensional MRI in Fig. 1 we can clearly detect that there are white tumor tissues at the chiasma. FCM (Fig. 1-1) and AFCM (Fig. 1-2) fuzzy algorithms both detected the tumor from the normal tissues using five clusters.

MRI medical imaging uncertainty is widely presented in the collected data because of the noise in the partial volume effects originating from the low resolution of the sensors. Another factor that causes uncertainty is the fact that frequently, the eyeball moves during the imaging and it is difficult to control this movement, especially in younger patients (infants). There, a distorted MR image (1) is presented in Fig. 2. It is difficult, but not impossible, for the naked eye to locate abnormalities in these images. If the FCM (Fig. 2-1) and AFCM (Fig. 2-2) algorithms are used, the abnormalities at the chiasma area can be detected with greater ease.

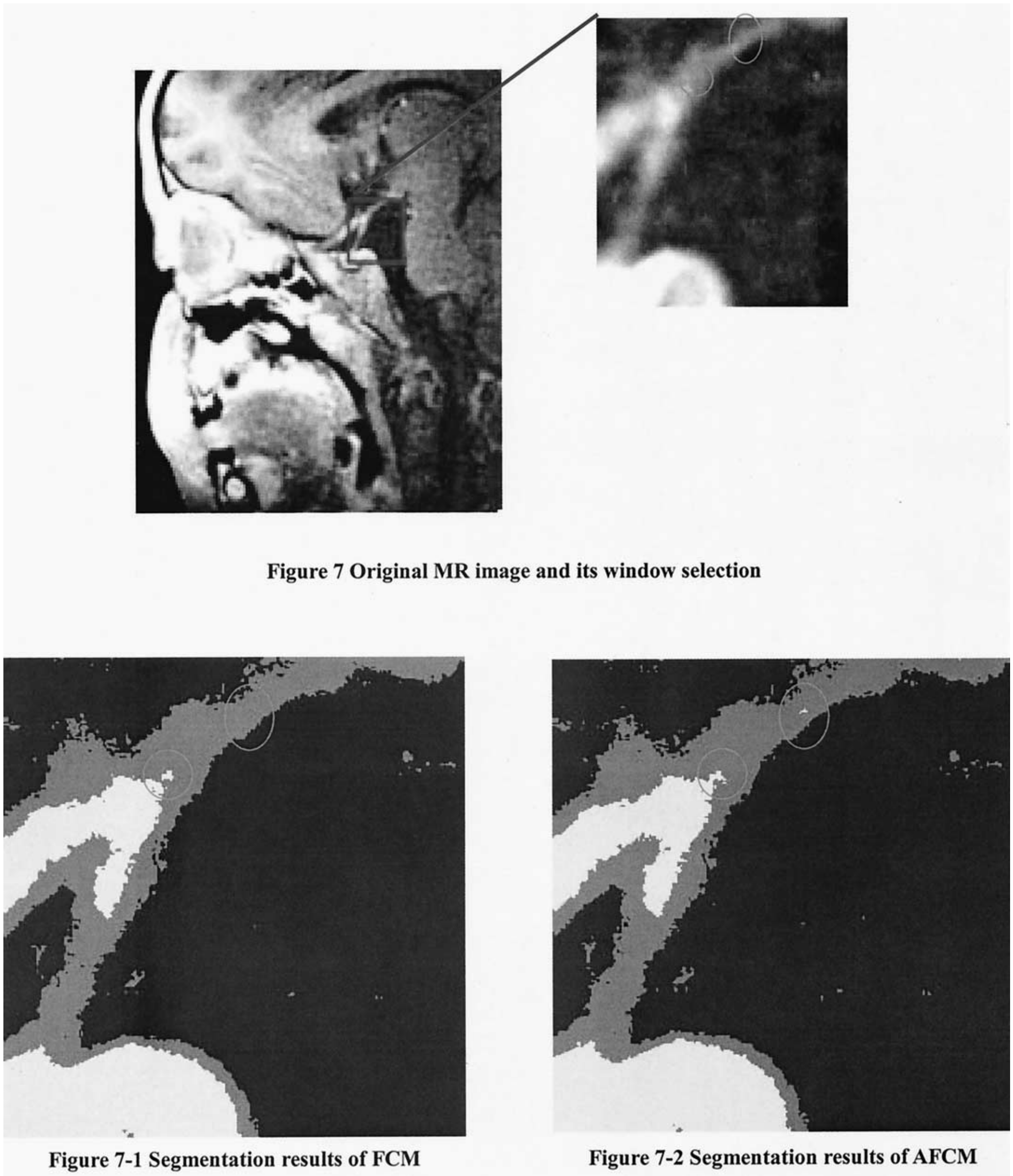

Figure 7 Original MR image and its window selection

Figure 7-1 Segmentation results of FCM

Figure 7-2 Segmentation results of AFCM

Fig. 7.

For the more distorted MR image (2) in Fig. 3, one can no longer locate the abnormalities using the naked eye. With the use of the FCM (Fig. 3-1) and AFCM (Fig. 3-2) algorithms, one can still detect the tumor tissues.

Fig. 4 is fuzzy on the tumor edge and neuron tissue. Usually some radio opacity around the tumor is suspected as tissue edema. The gray level is a little deeper than the normal neuron tissue. In the red circle in Fig. 4 it is difficult to tell whether there are abnormal tissues. Applying the FCM and AFCM algorithms to Fig. 4 produces Figs. 4-1 and 4-2. In these two segmentations there are no abnormalities. In the next part of this paper we will discuss why we chose to decrease the clusters from five to three clusters in our window selection.

With more clusters separating the tissue produces greater processing time. Using five clusters results in inefficient processing. Even worse is the fact that due to the natural movement of the tissues and the limitations of the sensors, as can be seen in Fig. 4, even though the tissues were separated into five clusters, no abnormalities appear. However, the specialist was suspicious that there was a tumor. Therefore we used a window selection scheme to solve this problem. The Fig. 5 in the first MRI data set is a window selection (296 $\times$ 161 pixels) from Fig. 1. The clusters were reduced into three types, connective tissue, nervous tissue and tumor tissue. The image was then enlarged, resulting in Fig. 5. We can see abnormalities in the red circle. After applying FCM and AFCM we produced Fig. 5-1 and Fig. 5-2 with the same results as Fig. 1.

Based on Figs. 4, 4-1 and 4-2, no tumor was detected from the normal tissues. However, the specialist was suspicious that there was a tumor. If we make a window selection from Fig. 4 we end up with Fig. 6. The abnormalities are not easily detectable. Processing Fig. 6 with FCM and AFCM results in Figs. 6-1 and 6-2. As the image of Fig. 6 shows, it is not clear but there is a shadow of tumor tissues. As can be seen in the segmentation using AFCM with Fig. 6-2, it is clear that there is a tumor. However, the FCM algorithm with Fig. 6-1 fails to detect a tumor. This shows that the AFCM algorithm is a better choice in this case.

Finally, we analyzed the second MRI data set (Fig. 7). This picture was processed with 283×292 pixels. From the picture, one lesion was clearly seen by MR image. However, some fuzzy shadows of lesions were suspected with tumor invasion. These suspected abnormalities are not easily detectable. For the purpose of detecting these abnormal tissues, a window of the area around chiasma is selected from the original MR image as shown in Fig. 7. The clusters were also of three tissue types as in Fig. 5. We then applied FCM and AFCM to the window selection picture and produced Fig. 7-1 and Fig. 7-2. We can see occult lesions (red circles) clearly enhanced with AFCM algorithm in Fig. 7-2. However, the FCM algorithm with Fig. 7-1 fails to show those occult lesions.

4. Discussion

Distant intracranial metastasis of Retinoblastoma tumor cells to optic chiasma region is a fatal disaster for the patient with intraocular Retinoblastoma. Even if the affected eyeball was enucleated, the patient should receive extra-chemotherapy or radiotherapy to cure the intracranial lesion to prevent this life threatening danger. Radio-opaque shadow illustrated on MRI brain scan is a hallmark of diagnostic clues. There are single or multiple foci of tumor particles lodged on the chiasma tissue. However, the radio-opaque signal on the chiasma region is sometimes obscured due to very small lesion-size or low radioactivity of radio-image reaction. From all these considerations, choosing unsupervised fuzzy clustering algorithms for MRI segmentation in Ophthalmology should be helpful to enhance the lesion for support diagnoses of the spread of occult lesions.

This paper used the best-known FCM and a newly proposed AFCM clustering algorithms as segmentation techniques for tissue differentiation in MRI of Ophthalmology. In general, both fuzzy clustering segmentation techniques can differentiate the tumor from the normal tissues. However, if MR images with motion cause too much blur and ambiguity or the tumor is too small to be easily detected, then both FCM and AFCM may fail to detect the tumor. For the purpose of detecting these suspected abnormalities, a window selection is preferable to isolate the problem area and enlarge the image. This window selection can decrease the cluster number and reduce the influence of the other tissue clusters to the small suspected tumor. Since AFCM tolerates clusters of unequal sample sizes better than FCM, AFCM is better in detecting small or blur suspected tumor based on a window selection. Overall, the physician is recommended to use window selection to isolate the problem area and enlarge the image and then separate the tissues using three tissue groups (connective, nervous and tumor) and apply the AFCM algorithm to the image for every Retinoblastoma patient.

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