Automatic brain MRI segmentation scheme based on feature weighting factors selection on fuzzy c-means clustering algorithms with Gaussian smoothing

Kai Xiao, Sooi Hock Ho* and Andrzej Bargiela

School of Computer Science, Faculty of Science,
University of Nottingham, Malaysia Campus,
Jalan Broga, 43500, Semenyih, Selangor, Malaysia
E-mail: kcx2kx@nottingham.edu.my
E-mail: Ho.Sooi-Hock@nottingham.edu.my
E-mail: abb@cs.nott.ac.uk
*Corresponding author

Abstract: In this paper we introduce a new clustering method and apply it to brain magnetic resonance imaging (MRI) lateral ventricular compartments segmentation. The method uses Gaussian smoothing to enable fuzzy c-mean (FCM) to create both a more homogeneous clustering result and reduce effect caused by noise. With the objective of finding the optimal clustering results, we present a weighted clustering scheme which is applied to a Gaussian smoothed image using bootstrapping approach of feature weighting. The scheme is called weighted FCM with Gaussian smoothing (WGFCM). In addition to the observations on the clustering results of the MR images, we use validity functions and clustering centroids to evaluate the clustering results. Compared with the standard FCM with or without Gaussian smoothing, we found that the proposed scheme provides a better clustering performance for brain MRI lateral ventricular compartments segmentation.

Keywords: fuzzy image processing; clustering; fuzzy c-means; weighting factors selection; Gaussian smoothing; clustering validity functions; bioinformatics.

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Biographical notes: Kai Xiao received his Master of Science in Information Technology from the University of Nottingham, Malaysia Campus in 2003. Currently, he is a Postgraduate Research Student and PhD candidate in the Faculty of Engineering and Computer Science of the University of Nottingham, Malaysia Campus. His research interests include medical image processing, pattern recognition and classification.

Sooi Hock Ho received his Bachelor of Electrical Engineering from the University of Malaya in 1978, and his Master of Computer Science from the University College, London in 1980. He worked in IBM Malaysia as a Specialist in the areas of operating systems and networking from 1981 to 2001, and has since joined the University of Nottingham, Malaysia Campus. His research interests include digital image processing, image compression and pattern recognition.

Andrzej Bargiela is a Professor and Director of Computer Science at the University of Nottingham, Malaysia Campus. He is a member of the Automated Scheduling and Planning Research Group in the School of Computer Science at the University of Nottingham. Since 1978 he has pursued research focused on processing of uncertainty in the context of modelling and simulation of various physical and engineering systems. His current research falls under the general heading of computational intelligence and involve mathematical modelling, information abstraction, parallel computing, artificial intelligence, fuzzy sets and neurocomputing.

1 Introduction

In medical image processing and analysis, segmentation is an indispensable step. magnetic resonance imaging (MRI) has become a particularly useful medical diagnostic tool for cases involving soft tissues, such as in brain imaging (Worth et al., 1997a; El-Baz et al., 2006; Bezdek et al., 1993; Caviness et al, 1989). Image segmentation is the process of assigning pixels to regions sharing common properties. MRI segmentation assumes great importance in clinical applications and scientific research projects. Despite the existence of many MRI segmentation frameworks, brain MRI segmentation is still a subject requiring intensive exploration due to the numerous challenges (Bezdek et al., 1993; Xiao et al., 2007a, 2007b; Liu et al., 2001; Brandt et al., 1994; Pham and Prince, 1999; Wu et al., 2003; Worth et al., 1997b).

The aim of this paper is to introduce a way to provide an improved solution on our previous works (Xiao et al., 2007a, 2007b) to automatically select optimal feature weighting factors using the method proposed by Hung et al. (2008) for both original and Gaussian smoothed image features. In addition to the observations of the clustering results, we applied several measurement methods such as clustering validity functions with added noise and measurements of displacement of clustering centroids due to noise, so as to provide objective evaluations of the clustering results from this scheme.

2 Background and related works

MRI segmentation assumes great importance in research and clinical applications. Noise, inhomogeneous pixel intensity distribution and blunt boundaries in the medical MR images caused by MR data acquisition process are the main problems that will affect the quality of MRI segmentation (Bouchachia and Pedrycz, 2006; Wu et al., 2003; Worth et al., 1997b). One principal source of noise is the ambient electromagnetic field picked up by the radiofrequency (RF) detectors acquiring the MR signal, and another is the object or body being imaged. Signal-to-noise ratio (SNR) is used as a synthetic index to quantify the totality of noise influence and to characterise the effectiveness of any MRI examination (Cai et al., 2007). As a result, added noise with specific SNR can be used for examining the clustering result affected by noise.

Fuzzy c-means (FCM) clustering method (Dunn, 1974; Bezdek, 1981) is a widely used unsupervised pattern recognition method for multi-spectral MRI segmentation (Bezdek et al., 1993). However standard FCM algorithm has several disadvantages. Firstly, it does not fully utilise the spatial information of an image, and is sensitive to noise. To improve the clustering result of FCM, Pedrycz and Waletzky (1997) took advantage of the available classified information and actively applied it as part of their optimisation procedures. Ahmed et al. (2002) modified the objective function of the standard FCM algorithm to allow the labels in the immediate neighbourhood of a pixel to influence its labelling. The modified FCM algorithm improved the results of conventional FCM methods on noisy images. However, the way in which they incorporate the neighbouring information limits their application to single-feature inputs.

Bouchachia and Pedrycz (2006) proposed a semi-supervised FCM method integrating kernel-based distance in the clustering algorithm. Chuang et al. (2006) applied the spatial information into the FCM algorithm by incorporating spatial function into the membership function to take advantage of correlation in image pixels neighbourhood to reduce the effect of noise and obtain more homogeneous clustering results.

Dulyakarn and Rangsanseri (2001) proposed a semi-supervised FCM algorithm which alternates between conventional FCM and FCM with spatial information. However in their modified membership functions, the way of summing up neighbouring pixels tends to blur the clustering result and degrades the edges. Another problem of applying this approach alone is that the feature weights are fixed and clustering results are unable to be tuned when multiple feature inputs are processed by the FCM algorithm.

Although the introduction of local spatial information to the corresponding objective functions enhances their insensitivity to noise to some extent, they are not completely immune to noise and outliers, especially in the absence of prior knowledge of the characteristics of the noise.

To alleviate this problem, Cai et al. (2007) further modified FCM algorithm and introduced a new way to make trade-off between the removal of noise and the preservation of details. However this method does not really take into account the multiple feature domains.

Since the FCM algorithm deals efficiently with multi-dimensional data, we proposed a study (Xiao et al., 2007a) based on the combination of the original and the Gaussian smoothed image data to improve clustering results. As the conventional FCM assumes equal importance of individual feature, the clustering performed on certain real world problems may not be acceptable. To make FCM perform better in such applications, we proposed a solution of adjustable feature weighting factors in one of our previous work (Xiao et al., 2007b). However, the computational burden associated with finding the optimal weights is significantly heavy through iteratively changing weighting factors. This is because the assessment of the validity of FCM results can be done only after the FCM computations are completed. The refinement of the weighting factors is therefore a slow process. However, our previous work (Xiao et al., 2007b) has demonstrated that FCM is sensitive to the selection of distance metric and optimal feature weight factors will lead to better clustering results. Therefore, an automatic method to find the optimal weighting factors is required.

Wang et al. (2004) applied a feature-weight learning approach based on a similarity measure proposed by Yeung and Wang (2002). More recently, Hung et al. (2008) proposed a feature-weights selection method based on statistical variations in the input data by using bootstrapping (Efron, 1979) approach and applied it to colour image segmentation.

Several previous works (Chuang et al., 2006; Worth et al., 1997b) have worked towards solving or alleviating these problems. To further improve the clustering results over the related works, in addressing the above mentioned problems and taking brain MRI lateral ventricular compartments as the case for the research, the novel weighted FCM (WGFCM) clustering scheme is designed to allow feature weighting factors automatically obtained for both original and Gaussian smoothed data set features.

3 FCM clustering: an overview

Data clustering is the process of dividing data elements into classes or clusters so that items between different classes are dissimilar as possible (Bezdek, 1974). Depending on the nature of the data and the purpose for which clustering is being used; similarity measure such as distance, connectivity, and intensity controls how the clusters are formed. FCM is a typical clustering method which groups one piece of data to two or more clusters, and associates with each element a set of membership levels. These membership levels indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters (Bezdek, 1974).

Let X ($x_1, x_2, x_3, \ldots, x_N$) denotes an image with N pixels to be partitioned into c clusters, where x_i represents multi-feature data. The algorithm is an iterative optimisation that minimises the cost function defined as follows:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \left\| x_j - v_i \right\|^2, \quad 1 \leq m < \infty, \tag{1}$$

where u_{ij} represents the degree of membership of data x_j in the i^{th} cluster, v_i is the *ith* cluster center, $\|*\|$ is a norm representing the Euclidean distance which expresses the similarity between measured multi-feature data and the cluster center (Bezdek et al., 1993; Chuang et al., 2006; Hung et al., 2008), and m is a real constant greater than 1 which controls the fuzziness of the resulting partition.

The membership function represents the probability that a pixel belongs to a specific cluster which depends on its distance from each cluster centers in the feature domain. The membership functions and cluster centers are iteratively updated until the cost function J_m in equation (1) is minimised as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{\frac{2}{m-1}}} \tag{2}$$

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \tag{3}$$

The iteration will stop when $\max\left\{ \left| J_{p+1} - J_p \right| \right\} < \sigma,$ where σ is the termination criterion between 0 and 1, and p is the iteration step.

4 Weighted FCMs with Gaussian blurring scheme

4.1 FCMs combined with Gaussian smoothing

The Gaussian 2-D convolution operator is used to blur or smooth image and remove detail and noise. A 2-D circularly symmetric Gaussian has the form:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e-\frac{x^2+y^2}{2\sigma^2} \tag{4}$$

It provides gentler smoothing and preserves edges better than a similarly sized mean filter because Gaussian function outputs a 'weighted average' of each pixel neighbourhood, with the average weighted more towards the value of the central pixel (Shapiro and Stockman, 2001; Xiao et al., 2007a). As the standard FCM algorithm supports multiple feature inputs, the original image and its Gaussian filtered image pixel values can be combined as a multi-dimensional matrix. By combining all the features into the multi-dimensional space, clustering results will be affected by both the original and the smoothed image data, becoming more noise-insensitive and homogeneous.

Algorithm 1 Feature weights adjustable FCM clustering

- Input: image *I*; array of feature data; array of feature weighting factors
- Set of number of clusters, *c*; number of maximum iterations, *max*
- Output: Set of clustered regions.

Set the initial membership value, u_{ij}

for $p = 1$ to *max* **do**

Update the new center points of clusters: $v_i = \dfrac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m}$;

Estimate the distance matrix: $D_{ij} = \sqrt{\sum_{k=1}^{M}\left(\alpha_k x_{jk} - v_{ik}\right)^2}$;

Calculate the cost function: $J_p = \sum_{j=1}^{N}\sum_{i=1}^{c} u_{ij}^m D_{ij}^2$;

Update the new membership function: $u_{ij} = \dfrac{1}{\sum_{k=1}^{c}\left(\dfrac{D_{ij}}{D_{kj}}\right)^{\frac{2}{m-1}}}$;

if $\left\{\left|J_{p+1} - J_p\right|\right\} < \sigma$ {convergence condition}

break;

end for

4.2 FCMs with adjustable feature weighting factors

4.2.1 Description

In the conventional FCM, as previously discussed, each input feature weighting to the standard Euclidean distance function is exactly the same. However in situations where one or more input features need to be emphasised, and other features to be diminished, the standard FCM algorithm is incapable of providing fine tuning for clustering.

By expressing $\left\| x_j - v_i \right\|$ with Euclidean distance function, D_{ij}, as in standard FCM, equation (1) can be expressed as:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} D_{ij}^{2} \tag{5}$$

where D_{ji} is the distance of data x_{jk} from center of *ith* cluster, v_{ik} in the *kth* dimension, N is the number of data points and M is the number of features

$$D_{ij} = \sqrt{\sum_{k=1}^{M} \left(x_{jk} - v_{ik} \right)^2} \tag{6}$$

To adjust the weighting of each input feature, equation (5) can be modified by adding factors α_k which becomes:

$$D_{ij} = \sqrt{\sum_{k=1}^{M} \left(\alpha_k x_{jk} - v_{ik} \right)^2} \tag{7}$$

Similar to the standard FCM algorithm, distances calculated by equation (5) will be used in all the steps of the FCM membership calculation.

4.2.2 Algorithm steps

The algorithm of adjustable feature weighting FCM is described as in Algorithm 1.

4.3 Bootstrapping approach to feature-weight selection

4.3.1 Description

It can be concluded from principal components analysis (PCA) that in multivariate analysis, greater variation in some features of the data provides important information.

Standard deviation is a usual measure on variability of a random sample, defined as

$$s = \sqrt{\frac{\sum_{j=1}^{n} \left(x_j - \bar{x} \right)^2}{n-1}}, \qquad \text{where } \bar{x} = \frac{1}{n} \sum_{j=1}^{n} x_j . \tag{7}$$

Using Karl Pearson's coefficient of variation which is independent of pure numbers, defined by

$$CV = \frac{s}{\bar{x}}. \tag{8}$$

For a random sample of $X_j = (x_{j1},\ldots, x_{jp})$ representing jth sample for $j = 1,\ldots, n$, then the coefficient of variation of k^{th} feature is defined as:

$$CV = \frac{\sqrt{\sum_{j=1}^{n}\left(x_{jk} - \bar{x}_k\right)^2 / (n-1)}}{\bar{x}_k}, \quad \text{where } \bar{x}_k = \frac{1}{n}\sum_{j=1}^{n} x_{jk}, \quad k = 1,\ldots, p \tag{9}$$

The k^{th} feature-weight can be defined as the expectation of normalised CV_k, i.e.,

$$w_k = E(W_k) = \int \omega dF_k(\omega), \quad \text{where } W_k = \frac{CV_k}{\sum_{k=1}^{p} CV_k}, \quad k = 1,\ldots, p \tag{10}$$

One of the method to estimate the value of w_k is by re-sampling the original data, X to create B number of replicate datasets by using bootstrapping method.

From the calculation of the sample mean of w_k for all B number of replication, the estimated feature weight w_k is found as below

$$\hat{w}_k = \frac{1}{B}\sum_{b=1}^{B} W_k(b), \quad \text{where } W_k(b) = \frac{CV_k(b)}{\sum_{k=1}^{p} CV_k(b)}, \quad k = 1,\ldots, p \tag{11}$$

4.4 Weighted fuzzy c-means and Gaussian smoothing (WGFCM)

4.4.1 Description

In many cases, there is only one input feature available for clustering, FCM needs to be tuned for an optimal clustering result while trying to be insensitive to noise. One feature can be combined with the Gaussian smoothed feature of itself to create an input data. Then the feature weights can be calculated using the bootstrapping approach of feature-weight selection to be applied into the FCM with adjustable feature weighting factors as the WGFCM, for fine tuning to achieve more optimised clustering results.

4.4.2 Algorithm steps

Algorithm 2 Combining Gaussian smoothed and original images by WGFCM

Input:

- image I
- set of number of clusters, *c*; number of maximum iterations, *max*
- size of Gaussian filter, *size* and value of Gaussian standard deviation, *sigma*
- estimated optimised feature weighting by bootstrapping of I and its Gaussian blurred data.

Output: Clustered optimised clustering result

1 Convert image data *I* to an array of original feature data, *Data*1

Algorithm 2 Combining Gaussian smoothed and original images by WGFCM (continued)

2	Create 2-D Gaussian low pass filter *PSF* by Gaussian kernel function F_{Gau} with *size* and standard deviation, *sigma*: $PSF = F_{Gau}(size, sigma);$
3	Convolve *Data*1 by the filter *PSF* to create Gaussian smoothed *Data*2: $Data2 = G(Data1, PSF);$
4	Create an input data array *Data* by combining *Data*1 and Gaussian smoothed *Data*2: $Data = [Data1, Data2];$ Find the estimated optimised feature weighting factors $\hat{w}_k = \frac{1}{B}\sum_{b=1}^{B} W_k(b)$ from bootstrapping of *Data* by equation (11).
5	Apply the feature weighting factors on WGFCM as described in *Algorithm 1*.

5 Validity functions for fuzzy clustering

5.1 Clustering validity functions based on partition coefficient and partition entropy

Fuzzy partition is used in this paper to evaluate the performance of clustering in a quantitative way. The representative functions for the fuzzy partition are partition coefficient V_{pc} (Bezdek, 1974) and partition entropy V_{pe} (Bezdek, 1975) defined as follows:

$$V_{pc} = \frac{\sum_{j=1}^{N}\sum_{i=1}^{c} u_{ij}^2}{N} \tag{12}$$

$$V_{pe} = \frac{-\sum_{j=1}^{N}\sum_{i=1}^{c}\left[u_{ij}\log u_{ij}\right]}{N}. \tag{13}$$

The idea of these validity functions is that the partition with less fuzziness means better performance. In both equation (9) and (10), u_{ij} (i = 1, 2,… c; j = 1, 2,… N) is the membership of data point j in cluster i. The closer this value is to unity the better the data are classified. As a result, the best clustering is achieved when V_{pe} is minimal and V_{pc} is maximal (Chuang et al., 2006).

5.2 Clustering validity functions based on geometric sample structure

The idea of validity functions based on measuring geometric data structure is that samples within one partition should be compact and samples between different clusters should be separate. To quantify the ratio of total variation within clusters and the separation of clusters, Fukuyama and Sugeno (1989) proposed Fukuyama-Sugeno validity function V_{fs}, Xie and Beni (Xie and Beni, 1991) proposed Xie-Benie validity function V_{xb}.

V_{fs} is defined as follows:

$$V_{fs} = \sum_{j=1}^{N}\sum_{i=1}^{c}\left(u_{ij}\right)^2\left(\left\|x_j - v_i\right\|^2 - \left\|v_i - \bar{v}\right\|^2\right) \tag{14}$$

and V_{xb} is defined as:

$$V_{xb} = \frac{\sum_{j=1}^{N}\sum_{i=1}^{c}\left(u_{ij}\right)^2\left\|x_j - v_i\right\|^2}{N * \left(\min_{i,k}\left\{\left\|v_k - v_i\right\|^2\right\}\right)}, \quad \text{where } v_i \neq v_k \tag{15}$$

An optimal clustering result generates samples that are within one cluster and samples that are separated between different clusters. Minimised V_{fs} or V_{xb} is expected to lead to a good partition.

Partition coefficient and partition entropy is a class of validation functions that uses only the membership function to evaluate the partitioning of the clusters. Their disadvantages are that it does not take into account the geometrical properties of the data and it depends monotonically on the number of clusters (Hoppner, 1999) while Fukuyama-Sugeno and Xie-Beni validity function however quantifies the performance of the clustering by taking into account the total variation within each clusters and the separation between clusters. Their main disadvantage is that it decreases monotonically when the number of clusters is very large (Xie and Beni, 1991).

6 Experimental results

The original images in Figures 1(a) and 1(b) were collected from (The Whole Brain Atlas, 2008). To focus on lateral ventricles segmentation, one pair of T1-weighted and T2-weighted MRIs in the trans-axial plane with the same slice number (which indicates they were taken from the same area of the brain) that displays the most noticeable lateral ventricular compartments were selected. To demonstrate the effect of noise when different feature weighting factors are applied on the segmentation processes, noisy images have been created by adding Gaussian white noise with a specific SNR value to the original images.

Conventional FCM with the combined features of T1 and T2 images as shown in Figures 2(a) and 2(b) is able to classify MRI images. However, the two parts of the lateral ventricular compartments as shown in Figures 3(a) and 3(c) are joined together in different levels; by combining the original image and the Gaussian smoothed image features, its counterpart as shown in Figures 3(b) and 3(d) shows the two fully separated compartments. Adding Gaussian smoothed image data into FCM with the selected feature weight factors reduces the number of spurious blobs, and the segmented images are more homogeneous.

Figure 4 shows the clustering result after applying standard FCM and WGFCM with feature weighting factors of $\alpha_1 = 0.5150$ / $\alpha_2 = 0.4850$ to noise contained MRI under 4 clusters.

It can easily be seen that the standard FCM creates a lot more wrong clusters due to the effect from added noise. In Figure 5, inside the segmented ventricular compartment as can be seen in Figure 5(b), the clustering result retrieved from WGFCM has much less pixels of other clusters than its counterpart in Figure 5(a).

Figure 1 (a) T1 and (b) T2 original images. (c) T1 and (d) T2 images added with noise of SNR = 10

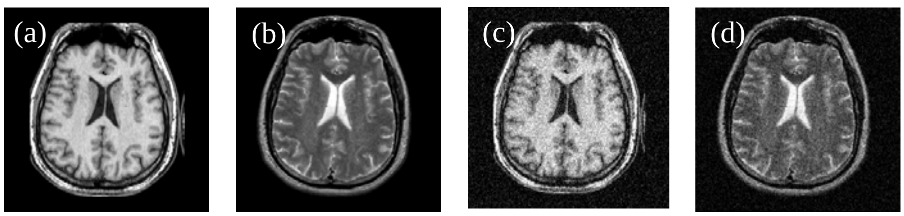


Figure 2 Segmented images of MRI images using FCM with features of (a) T1 + T2 images under 3 clusters; (b) T1 + T2 images under 5 clusters; (c) WGFCM with weighting factors of 0.5066/0.4934 on T1 image under 3 clusters, Gaussian filter kernel in size of 5 and sigma of 5; (d) WGFCM with weighting factors of 0.5063/0.4937 on T2 image under 5 clusters, Gaussian filter kernel in size of 5 and sigma of 5

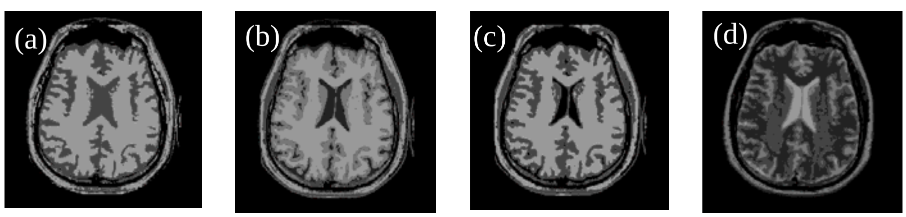


Figure 3 Extracted lateral ventricular compartments after FCM clustering with features of (a) T1 + T2 images under 3 clusters; (b) WGFCM with weighting factors of 0.5066/0.4934 on T1 image under 3 clusters, Gaussian filter kernel in size of 5 and sigma of 5; (c) T1 + T2 images under 5 clusters; (d) WGFCM with weighting factors of 0.5063/0.4937 on T2 image under 5 clusters, Gaussian filter kernel in size of 5 and sigma of 5

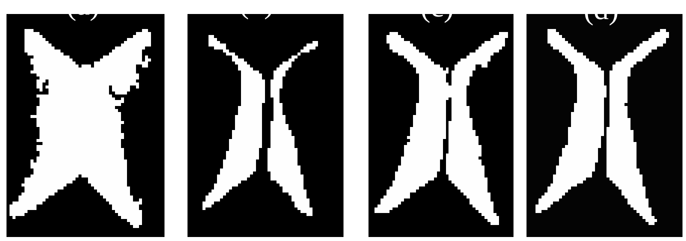


Figure 4 Segmented images of noisy of SNR = 10, MR images using FCM with features of T1 images under 4 clusters by: (a) standard FCM; (b) WGFCM of $\alpha_1 = 0.5150$ / $\alpha_2 = 0.4850$ under 4 clusters

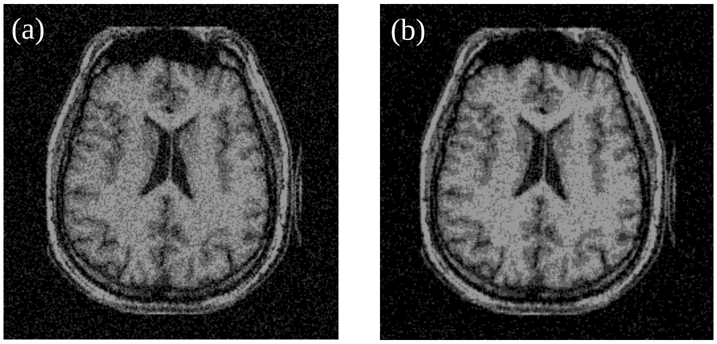


Figure 5 Clustering results of using original T2 MRI with SNR = 5 noise added as input features under 4 clusters by: (a) standard FCM; (b) WGFCM with feature weighting factors of $\alpha_1 = 0.5365$ / $\alpha_2 = .0.4635$

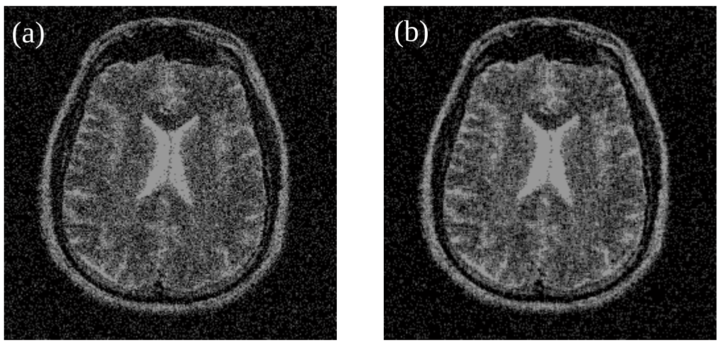
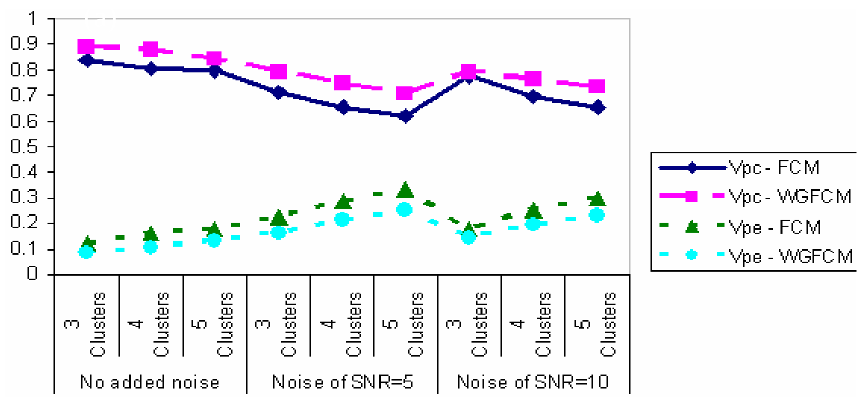
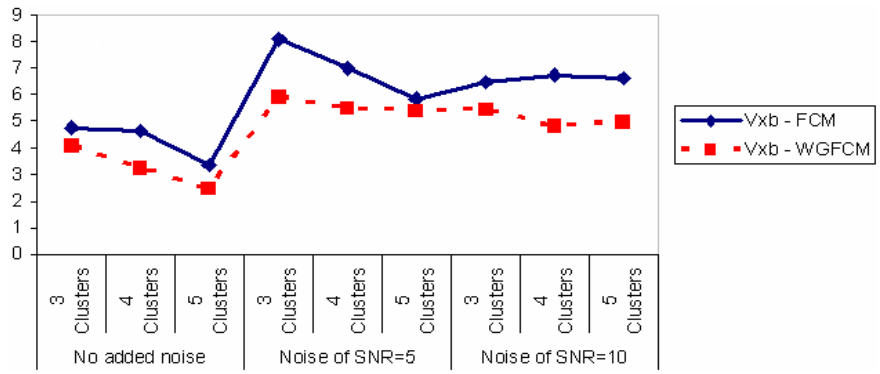


Figure 6 Comparison of the validity functions result of (a) V_{pc} and V_{pe} (b) V_{xb} for clustering results of images using FCM and WGFCM (see online version for colours)



(a)

Figure 6 Comparison of the validity functions result of (a) V_{pc} and V_{pe} (b) V_{xb} for clustering results of images using FCM and WGFCM (continued) (see online version for colours)



(b)

Table 1 Centroids values retrieved in FCM and WGFCM on original or noise added MR images

	Standard FCM on original image		*Standard FCM on original image with added noise*		*WGFCM on original image with added noise*	
	Feature 1	*Feature 2*	*Feature 1*	*Feature 2*	*Feature 1*	*Feature 2*
Centroid value	1.1228	1.179	7.2773	11.6389	7.0639	17.4937
Centroid value	62.2946	172.9436	48.4892	130.1352	82.8444	149.0547
Centroid value	83.72	42.537	88.2646	21.1917	83.2317	22.5638
Centroid value	139.724	107.9093	155.6065	119.1692	123.1686	94.1849
Centroid value	197.7957	83.5036	227.2078	81.0297	221.1783	88.7781

Table 2 Clustering validity function evaluation on standard FCM on T1 + T2 MRI and WGFCM with Gaussian smoothed T1 with filter kernel in size of 5 and sigma of 5

Cluster number	*FCM type with*	V_{pc}	V_{pe}	V_{xb}	V_{fs}
3	*Standard FCM on T1+T2*	0.8400	0.1234	4.7732	–2.6645e+008
	WGFCM on T1+T2	0.8872	0.0894	4.1038	–4.4116e+008
4	*Standard FCM on T1+T2*	0.8073	0.1593	4.63865	–3.0245e+008
	WGFCM on T1+T2	0.8703	0.1087	3.2298	–4.5236e+008
5	*Standard FCM on T1+T2*	0.7967	0.1789	3.32675	–3.0693e+008
	WGFCM on T1+T2	0.8498	0.1299	2.4717	–4.5440e+008

Table 3 Clustering validity function evaluations on standard FCM and WGFCM on brain MRIs with added noise

Image	*Cluster number*	*FCM type*	V_{pc}	V_{pe}	V_{xb}	V_{fs}
Noise added MR images SNR = 5	3	*Standard FCM on T1+T2*	0.7119	0.2252	8.1326	–1.522e+008
		WGFCM on T1+T2	0.7914	0.1666	5.9239	–3.152e+008
	4	*Standard FCM on T1+T2*	0.6570	0.2883	6.9921	–1.677e+008
		WGFCM on T1+T2	0.7387	0.2175	5.4691	–3.248e+008
	5	*Standard FCM on T1+T2*	0.6198	0.3349	5.8634	–1.782e+008
		WGFCM on T1+T2	0.6935	0.2642	5.3856	–3.260e+008
Noise added MR images SNR = 10	3	*Standard FCM on T1+T2*	0.7787	0.1769	6.4997	–2.017e+008
		WGFCM on T1+T2	0.8404	0.1304	5.4512	–3.681e+008
	4	*Standard FCM on T1+T2*	0.6932	0.2551	6.7743	–1.822e+008
		WGFCM on T1+T2	0.7753	0.1875	4.7989	–3.495e+008
	5	*Standard FCM on T1+T2*	0.6557	0.2962	6.6712	–1.938e+008
		WGFCM on T1+T2	0.7328	0.2270	4.9956	–3.467e+008

7 Analytical comparison and discussion

To evaluate the noise sensitivity of WGFCM against conventional FCM, T1- and T2-weighted MR images as shown in Figures 1(a) and 1b) are added with noise of SNR = 5. Firstly using original images as input features for standard FCM clustering, the retrieved centroid values are recorded. Noise added images are then applied as input features for conventional FCM and WGFCM clustering.

Figure 6 compares the validity functions result used to evaluate the performance of FCM clustering for six images. Based on the rules of validity functions measurements where 'The best clustering is achieved when V_{pe} and V_{xb} is minimal and V_{pc} is maximal' the clustering results are better for WGFCM than the standard FCM with features from T1 and T2 images.

Due to the fact that added noise will cause the centroid value of each cluster to be changed after FCM clustering, each corresponding centroid is displaced after noise is added. The sensitivities to noise of FCM and WGFCM can then be compared by the mean of each cluster centroids displacement. Table 1 tabulates the retrieved centroids values. It can be calculated that the average displacement in conventional FCM and

WGFCM are 25.585 and 22.866, respectively. WGFCM is showing stronger insensitivity to noise than conventional FCM.

As can be seen in Table 2 and Table 3, whether using original or noise added MR images, the validity functions results retrieved from WGFCM clustering method for V_{pc} is greater, and V_{pe}, V_{fs} and V_{xb} are less than that from standard FCM. This shows that in WGFCM, better clustering performance and more noise-insensitive results can be obtained.

As a result, FCM with adjustable feature weights allows validity functions to find appropriate weighting factors to correct the errors in the classification caused by noise.

8 Conclusions

FCM is one of the most well-known clustering algorithms. But it is sensitive to noise and its performance is limited by the equal feature weights of the standard FCM. To make this method more suitable for the application of brain MRI ventricular compartments segmentation, an intensive study on Gaussian smoothed image with weighting factors selection using bootstrapping approach known as WGFCM is conducted. The method was experimented on MRI images with and without added noise. Apart from observation of the clustering results in the specific application of brain ventricular compartment segmentation, clustering centroid movements caused by the added noise, and four clustering validity functions are measured. Results show that our proposed WGFCM scheme is more insensitive to noise and leading to better clustering performance.

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