CHAPTER 5

GENERALIZED KERNEL FUZZY C-MEANS
CLUSTERING WITH IMPROVED FUZZY PARTITION
FOR MEDICAL IMAGE SEGMENTATION

5.1 PROLOGUE

The generalized FCM (GFCM) does not consider any spatial information in image context, which makes it very sensitive to noise, outliers and other imaging artifacts. Due to not taking account of any spatial information in image context, GFCM is sensitive to noise in gray images. In order to make GFCM robust to noise in gray images, a kernel version of GFCM with spatial information for image segmentation has been used. The spatial information derived from the image was introduced into the fuzzy similarity measure to improve the segmentation performance of spectral clustering on images corrupted by noise.

5.2 INTRODUCTION

In FCM algorithm, is sensitive to noise and outliers. Data points which are not close to any cluster center are said to be noise or outliers. Outliers are data points which are significantly deviated from the remaining data points. Gathering the noise points as a separate cluster by a specific mathematical method is called noise clustering. The concept of noise clustering algorithm is the introduction of noise cluster that will contain noisy data points. Data points whose distance to all clusters exceeds a certain threshold are considered as noise. This distance is called noise distance.
The objective function in the fuzzy C-means algorithm has one major drawback which is that it does not contribute to any of the clusters in the whole dataset but still has a great impact on the cluster formation as the cluster memberships for each individual data need to sum up to one. This is not advantageous because data sets in real applications contain noisy data points. When the data point is an outlier then the sum of membership values of each data point for the entire clusters is equal to 1 which is not possible because the outlier is not close to any cluster center having very low membership grade.

To overcome this drawback in the last few years some clustering algorithms have been introduced which are robust against noise and outliers. One of the improved versions of FCM algorithm has been proposed by Dave (1991), to overcome the major deficiency of the FCM algorithm, its noise sensitivity. In this algorithm, the noise cluster is represented by a fictitious prototype that has a constant distance d from all the data points. Thus an object belongs to a good cluster only if there exists a prototype such that its distance from the data point is less than d, otherwise the data point belongs to the noise cluster. In robust FCM algorithm, the noise distance d is constant. It is obvious that no constant value will be appropriate to cover all noisy data points. If the constant value d is too large, robust FCM degenerates to standard FCM and outliers are forced to belong to real clusters. If d is too small, a lot of data points in the whole set can be considered as noise and misplaced into noise cluster. Therefore the noise distance d is a critical parameter of the algorithm and should be determined carefully.

Image segmentation plays an important role in pattern recognition, computer vision and image understanding fields (Pal et al. 1993) (Zhang et al. 2008). Among many segmentation algorithms, clustering approaches are one of the first techniques used for the nature or texture image segmentation
because of its simplicity and efficiency. As one of the most widely used clustering methods, the fuzzy c-means clustering algorithm (FCM) (Bezdek 1981) introduces the fuzziness for the belongingness of each image pixel and can retain more information from the original image than the hard c-means clustering algorithm (HCM). In the last few decades, many newly proposed fuzzy clustering algorithms (Fan et al. 2003) (Zhu et al. 2009) originate from FCM. However, the standard FCM does not consider any spatial information in image context, which makes it very sensitive to noise, outliers and other imaging artifacts. Selection of a suitable approach to a segmentation problem can be a complicated dilemma. Clustering is a popular unsupervised classification method and has found

Clustering algorithm attempts to classify a voxel to a tissue class by using the notion of similarity to the class. Since there is no information given about the underlying data structure or the number of clusters, there is no single solution to clustering, neither is there a single similarity measure to differentiate all clusters. Therefore for this reason there is no theory which illustrates clustering uniquely. This paper has used the paradigm of fuzzy clustering which is based on the elements of fuzzy set theory for segmenting medical images. Fuzzy based clustering methods (Al-sultan et al. 1997) (Al-sultan et al. 1993) (Boudraa et al. 1996) (Weijie chen et al. 2006) have attracted more attention for image segmentation techniques, because they gathered more information from the image (Pham et al. 2000). Because of Euclidian distance based objective function of standard FCM, it works well in clustering the noise free data and it fails to cluster the dataset degraded by noise.

Zhao et al. (2011) also proposed several fuzzy clustering algorithms with spatial information, in which a kind of spatial information called nonlocal spatial information is introduced into fuzzy clustering. Wang and Bu
(2010) established a local spatial similarity measure model to adaptively
determine the initial cluster center and initial membership and utilized the
inherent high inter-pixel correlation to modify the fuzzy membership. Zhao et
al. (2011) utilized the fuzzy membership degree values of pixels to define a
novel similarity measure for spectral clustering, which is called fuzzy
similarity measure. Subsequently, the spatial information derived from the
image was further introduced into the fuzzy similarity measure to improve the
segmentation performance of spectral clustering on images corrupted by noise
(Liu et al. 2012).

Cai et al. (2007) proposed the fast generalized FCM (FGFCM)
algorithm. This method introduces a local similarity measure that combines
both spatial and gray level information to form a non-linearly weighted sum
image. Clustering is performed on the basis of the gray level histogram of the
summed image. Thus, its computational time, similar to EnFCM, is also very
small. However, these algorithms do not directly apply on the original image.
They need some parameters to control the trade-off between robustness to
noise and effectiveness of preserving the details. The selection of these
parameters is not an easy task, and has to be made by experience or by using
the trial-and-error method. To overcome the above mentioned problems,
krinidis et al. (2010) presents a novel robust fuzzy local information c-means
clustering algorithm (FLICM), which is free of any parameter selection, as
well as promoting the image segmentation performance.

In order to further improve the performance of FLICM in
restraining noise, another novelty in this study is introducing the kernel
distance measure to its objective function. In recent years, kernel methods
have received an enormous amount of attention in machine learning
community. Its main idea is to transform complex nonlinear problems in
original low dimensional feature space to the problems easily solved in the
transformed space. Typical examples are support vector machines (SVM) (Cristianini et al. 2000) (Yang & Zhang 2011) kernel principle component analysis (KPCA) (Roth & Steinhage 2000) and kernel perceptron algorithm (Scholkopf et al. 1998). Particularly, the clustering algorithms based on the kernel methods have been shown to be robust to the outliers or noises of the dataset (Wu & Yang 2002).

5.3 **FCM BASED SEGMENTATION TECHNIQUES**

5.3.1 **Conventional FCM Clustering Algorithm**

Multiresolution segmentation is a bottom up region merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into bigger ones. Throughout this pair wise clustering process, the underlying optimization procedure minimizes the weighted heterogeneity of resulting image objects, where $n$ is the size of a segment and $h$ an arbitrary definition of heterogeneity (Bezdek 1981). In each step, that pair of adjacent image objects is merged which stands for the smallest growth of the defined heterogeneity. If the smallest growth exceeds the threshold defined by the scale parameter, the process stops. Doing so, multi-resolution segmentation is a local optimization procedure. The entropy based methodology for segmentation of satellite images is performed as follows. Images are divided into square windows with a fixed size $L$, the entropy is calculated for each window, and then a classification methodology is applied for the identification of the category of the respective windows. The classification approach can be supervised or non-supervised. Supervised classification needs a training set composed by windows whose classes are previously known (prototypes), such as rural and urban areas.

Given a data set $X = \{x_1, x_2, \ldots, x_n\}$, where the data point $x_j \in \mathbb{R}^p (j = 1, \ldots, n)$, $n$ is the number of data, and $p$ is the input dimension of a data
point, traditional FCM (Bezdek 1981) groups $X$ into $c$ clusters by minimizing the weighted sum of distances between the data and the cluster centers or prototypes defined as

$$Q = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij})^{m} \|x_j - o_i\|^2$$  \hspace{1cm} (5.1)

Here, $\|\|$ is the Euclidean distance. $u_{ij}$ is the membership of data $x_j$ belonging to cluster $i$, which is represented by the prototype $o_i$. The constraint on $u_{ij}$ is 1 and $m$ is the fuzzification coefficient.

### 5.3.2 Kernel FCM (KFCM)

When applying the KFCM framework in image-segmentation problems, the multiresolution segmentation may end up with local optimization procedure. Global mutual fitting is the strongest constraint for the optimization problem and it reduces heterogeneity mostly over the scene following a pure quantitative criterion. Its main disadvantage is that it does not use the treatment order and builds first segments in regions with a low spectral variance leading to an uneven growth of the image objects over a scene. It also causes an unbalance between regions of high and regions of low spectral variance. Comparison of global mutual fitting to local mutual fitting results show negligible quantitative differences, the former always performs the most homogeneous merge in the local vicinity following the gradient of the degree of fitting. The growth of image objects happens simultaneously as well in regions of low spectral variance as in regions of high spectral variance.

KFCM confines that the prototypes in the kernel space are actually mapped from the original data space or the feature space. That is, the objective function is defined as
\[ Q = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \| \varphi(x_{i}) - \varphi(o_{j}) \|^2 \]  

(5.2)

The objective function is then reformulated as

\[ Q = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} (1 - k(x_{i}, o_{j})) \]  

(5.3)

Here, \((1 - k(x_{i}, o_{j}))\) can be considered as a robust distance measurement derived in the kernel space.

5.3.3 Multiple Kernel FCM (MKFCM)

The application of multiple or composite kernels in the FKM has its advantages. In addition to the flexibility in selecting kernel functions, it also offers a new approach to combine different information from multiple heterogeneous or homogeneous sources in the kernel space. Specifically, in image-segmentation problems, the input data involve properties of image pixels sometimes derived from very different sources. Therefore, we can define different kernel functions purposely for the intensity information and the texture information separately, and we then combine these kernel functions and apply the composite kernel in MKFCM to obtain better image-segmentation results. Examples that are more visible could be found from multitemporal remote sensing images. The pixel information in these images inherits from different temporal sensors. As a result, we can define different kernels for different temperature channels and apply the combined kernel in a multiple-kernel learning algorithm.

The general framework of MKFCM aims to minimize the objective function
\[
Q = \sum_{i=1}^{\alpha} \sum_{j=1}^{N} u_{ij} \| \phi_{\text{com}}(x_i) - \phi_{\text{com}}(Q) \|^2
\]  

(5.4)

To enhance the Gaussian-kernel-based KFCM-F by adding a local information term in the objective function

\[
Q = \sum_{i=1}^{\alpha} \sum_{j=1}^{N} u_{ij} \left(1 - k(x_j, Q)\right) + \alpha \sum_{i=1}^{\alpha} \sum_{j=1}^{N} u_{ij} \left(1 - k(x_j, Q)\right)
\]  

(5.5)

where \(x_j\) is the intensity of pixel \(j\). In the new objective function, the additional term is the weighted sum of differences between the filtered intensity \(x_j\) (the local spatial information) and the clustering prototypes. The differences are also measured using the kernel induced distances. Such kind of enhanced KFCM-based algorithm is denoted as AKFCM (with a standing for additional term).

It is worth noting that \(k_1\) or \(k_2\) in the first variant of MKFCM-K-based image segmentation can be changed to any other Mercer kernel function for the information related to image pixels. This empowers the flexibility to the segmentation algorithm in kernel function selections and combinations. For example, a composite kernel that joins different shaped kernels can be defined as

\[
k_{\text{com}} = k_1 + \alpha k_2
\]  

(5.6)

where \(k_1\) is still the Gaussian kernel for pixel intensities

\[
k_2(x_i, x_j) = e^{-\frac{|x_i - x_j|^2}{\sigma^2}}
\]  

(5.7)

\(k_2\) is a polynomial kernel for the spatial information.
\[ k_2(x_i, x_j) = (x_i x_j + d)^2 \]  
(5.8)

If \( k_{\text{com}} = k_1 + \alpha k_2 \) is the composite kernel, the minimized objective function of the MKFCM is derived as

\[ Q = \sum_{i=1}^{N} \sum_{j=1}^{N} u_{ij}^\alpha \| \phi_{\text{com}}(x_i) - o_j \|^2 \]  
(5.9)

For example, the input image data \( x_i \) is set to be \( x_i = [x_i, x_i, x_i] \in \mathbb{R}^3 \), the same as the third variant of MKFCM, then the composite kernel is designed as

\[ K_i = w_1 \phi K_1 + w_2 \phi K_2 + \ldots + w_p \phi K_p \]  
(5.10)

The MKFCM algorithm evaluates the centroids so as to minimize the influence of outliers. Unlike FCM, it does not attempt fuzzification for elements having membership values above the calculated threshold. This reduces the computational burden compared to FCM also there is an absence of external user-defined parameters. The removal of this initial trial and error factor makes MKFCM more robust, as well as insensitive to the fluctuations in the incoming data. The elevation and reduction of the membership values to 1 and 0, respectively, results in contrast enhancement in the observability of the incoming data. This helps in focusing on the ambiguous boundary region, thereby gaining in terms of the quality of segmentation. To further improve the performance of segmentation, MKFCM that linearly combines three kernels, i.e., the first two kernels are the kernels for intensities and the local spatial information. To sum up, the merit of MKFCM-based image-segmentation algorithms is the flexibility in selections and combinations of the kernel functions in different shapes and for different pieces of information. After combining the different kernels in the kernel space, there is no need to change the computation procedures of MFKCM.
This is another advantage to reflect and fuse the image information from multiple heterogeneous or homogeneous sources. MKFCM-based image-segmentation algorithms are inherently better than other KFCM-based image segmentation methods. The MKFCM’s significant flexibility in kernel selections and combinations and the great potential of this flexibility could bring to image segmentation problems. In the MKFCM framework, we can easily fuse the texture information into segmentation algorithms by just adding a kernel designed for the texture information in the composite kernel. As in the satellite image-segmentation and two-texture image-segmentation problems, simply adding a Gaussian kernel function of the texture descriptor in the composite kernel of MKFCM leads to better segmentation results.

5.3.4 Modified Adaptive FCM (MAFCM)

In this type of clustering, the objective function to be minimized is given below.

\[
J_{MAFCM} = \sum_{k=1}^{c} \sum_{i=1}^{n} (C_T u_{ik}^{m} + C_T t_{ik}^{m} + \| \mathbf{t}_k - \mathbf{v}_i \|^2 + \sum_{i=1}^{c} \gamma_i \sum_{k=1}^{n} (1 - \epsilon_{ik}))
\]

(5.11)

where \( \mathbf{V} = \{v_1, v_2, \ldots, v_l\} \) is the characterized intensity center. The parameters \( C_T > 0 \), \( C_T > 0 \), \( m > 1 \), \( \eta > 1 \), the \( \epsilon_{ik} > 0 \) are user-defined constants. The constants \( C_T \) and \( C_T \) define the relative importance of fuzzy membership and typicality values in the objective function.

Note that \( u_{ik} \) has the same meaning of membership as that in FCM. Similarly, \( t_{ik} \) has the same interpretation of typicality as in PCM. Let, the objective function of PFCM can get the minimum by updating the membership \( U \), the typicality \( T \) and the cluster centers \( V \) as follows:
\[ u_{ik} = \left( \sum_{j=1}^{m} \left( \frac{d_{ij}}{d_{ij}^m} \right)^{-\frac{1}{m-1}} \right)^{-1} \] (5.12)

\[ v_{ik} = \frac{1}{1 + \left( \frac{C_{ik}}{b_{ik}} \right)^d} \] (5.13)

\[ y_i \text{ is defined as} \quad y_i = \frac{(w^+_{i+})^N = \sum_{k=1}^{N} w_{ik}^m D_{ik}}{\sum_{k=1}^{N} w_{ik}^m} \] (5.14)

The intensity \( I_k \) at location \( k \) far away from the neighborhood center should have less influence in the clustering criterion function than the locations close to the neighborhood center.

### 5.4 GENERALIZED FUZZY C-MEANS CLUSTERING ALGORITHM

The generalized fuzzy c-means clustering (GFCM) algorithm with improved fuzzy partition greatly improves the performance of kernel fuzzy c-means clustering algorithm (KFCM). GFCM under appropriate parameters can converge more rapidly than FCM. To make GFCM robust to noise in gray images, GFCM was incorporated with the local information derived from the image (Zhao and Jiao 2011). In order to further improve the insensitivity of GFCM to noise in gray images, a kernel version of GFCM with spatial information is proposed. By introducing the spatial constraint term, it behaves more robust than GFCM in the noisy gray image segmentation. In this modified method, first a term about the spatial constraints derived from the image is introduced into the objective function of GFCM, and then the kernel induced distance is adopted to substitute the Euclidean distance in the new objective function. In this clustering, the non-Euclidean structures in data are included to enhance the robustness of the original clustering algorithms to reduce noise (Thakur and Lingam 2013).
Though the conventional FCM algorithm works well on most noise-free images, and KFCM algorithms have excellent performance in the applications by given appropriate kernel function and reasonable parameters. But, the KFCM algorithm described in previous section still has one drawback: it is very sensitive to noise and other imaging artifacts, since it does not consider any information about neighbourhood term. Using the KFCM algorithm on image segmentation, the calculation of $J_{km}$ only consider the pixels of $X_k$, in fact, the neighbour around of the $X_i$ have the implied relationship to the $X_i$.

As a consequence the KFCM algorithm is unsuitable for images corrupted by impulse noise. In order to overcome this problem, we propose a generalized kernel based fuzzy c means (GKFCM) algorithm which incorporates local information into its objective function, defined in terms of $J_{GKFCM}$ as follows:

Chen and Zhang (2004) introduced a local spatial constraint term where $x_j$ denotes the spatial information of the pixel $x_j$, into the objective function of FCM to make FCM robust to noise in the image. In (Zhao and Jiao 2011), GFCM was incorporated with this spatial constraint term and the objective function of GFCM_S with spatial information was presented as follows.

$$J_{GFCM_S} = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}^m \|x_j - \theta_i\|^2 + \sum_{j=1}^{c} a_j \sum_{i=1}^{n} w_{ij}(1 - w_{ij}^{m-1}) + \beta \sum_{j=1}^{n} \sum_{i=1}^{n} w_{ij}^m \|x_j - \theta_i\|^2$$

(5.15)

The third term is the spatial constraint term, in which the parameter $\beta$ controls the penalty effect of the spatial constraint. In this work, the mean (median) of the neighbors within a specified window around the pixel $x_j$ is
used to represent \( x_p \) and denote GFCM with the mean (median) spatial information as GFCM-S. Through kernel substitution, the objective function of kernel generalized fuzzy c-means clustering with spatial information (KGFCM_S) is given as follows

\[
J_{\text{KGFCM}_S} = 2 \sum_{i=1}^{N} \sum_{j=1}^{N} u_{ij}^m \left( 1 - K(x_i, \theta_j) \right) + \sum_{i=1}^{N} \alpha_i \sum_{j=1}^{N} u_{ij} \left( 1 - u_{ij}^{m-2} \right) + \beta \sum_{i=1}^{N} \sum_{j=1}^{N} u_{ij}^m \| x_i - \theta_j \|^2
\]

(5.16)

The equation (5.17) can be validated by determining the characterized intensity \( \theta_j \). To determine the \( \theta_j \) value, the \( J_{\text{KGFCM}_S} \) is converted into unconstrained form \( L \). By taking partial derivative of \( L \) with respect to \( v_i \) and setting it to zero,

\[
\frac{\partial L}{\partial \theta_j} = 0 \Longleftrightarrow \sum_{i=1}^{N} u_{ij}^m K(x_i, \theta_j) (x_i - \theta_j) + \beta \sum_{i=1}^{N} u_{ij}^m K(x_i, \theta_j) (x_i - \theta_j) = 0
\]

(5.17)

\[
\theta_j = \frac{\sum_{i=1}^{N} u_{ij}^m K(x_i, \theta_j) x_i}{\sum_{i=1}^{N} u_{ij}^m K(x_i, \theta_j) \| x_i - \theta_j \|^2}
\]

(5.18)

It is clearly shown that the corresponding membership values of the noisy, as well as of the no-noisy pixels gradually tend to a similar value after iteration by iteration, ignoring the noisy pixels. And after five iterations the algorithm converges. In such case, the gray level values of the noisy pixels are different from the other pixels within the window, while the fuzzy factor balances their membership values. Thus, all pixels within the window belong to one cluster. Therefore, the combination of the spatial and the gray level constraints incorporated in the factor \( K \) suppress the influence of the noisy
pixels. Moreover, the factor $K$ is automatically determined rather than artificially set, even in the absence of any prior noise knowledge.

5.5. RESULTS AND DISCUSSION

The kernel generalized fuzzy c-means clustering with spatial information (KGFCM_S) based segmentation and for test images and medical images. We test and compare the proposed method with some other reported algorithms on several synthetic images and synthetic brain MR images from two aspects. The performance of FCM-type algorithms depends on the initialization, this work does the initialization and iterations depend upon the input images and choose the one with the best objective function value. This increases the reliability of comparison results acquired in the simulations. The main goals of an image segmentation algorithm are optimization of segmentation accuracy and its efficiency. Considering accuracy, the proposed method is concentrated on obtaining a robust segmentation for noisy images and a correct detection of small regions. The segmentation result with Gaussian noise for different images are shown in Fig.5.1. The noise factor considered for the Gaussian noise is $[0.0125]$ (Karayannis 1995).
The parameter α is a constant, which controls the influence of the global intensity force and local intensity force. When the intensity inhomogeneity is severe, the bias estimation relies on the local intensity force.
In such case, we should choose small $\alpha$, as the weight of the global intensity force. Otherwise, the bias field estimation may perform poorly. For images with minor inhomogeneity, the accuracy of segmentation relies on the global intensity force. In this case, we can use relatively larger, as the weight of global intensity. Thus, the global intensity reduces the misclassification for the pixels around the edges. The performances of these ten methods under $m = 2$ are first evaluated. For the Gaussian noisy image, FCM and GFCM are both sensitive to noise and their segmentation results are not satisfying.

Figure 5.1 Segmentation result of KGFCM_S with gaussian noise (0,0.0125) for a) test image b) flower c) MRI image1 d) MRI image2

The proposed KGFCM_S outperforms FCM and GFCM in segmentation performance and running time. Especially, the methods using the mean spatial information are more suitable for the image corrupted by the Gaussian noise than the methods using the median spatial information.
Moreover, under the same spatial information, these kernel methods utilizing the spatial information outperform the methods only utilizing the spatial information in segmentation performance. Test images and medical images, with 256×256 pixels are considered. The two images are corrupted by Salt and Pepper and Gaussian noise.

The number of clusters has smoother regions and much clearer image edge while removing almost added noise. Visually, the smallest value \( E \) can be obtained using the proposed method, which can remove the noise while preserving significant image details and obtain the good performance. Furthermore, it is relatively independent of the type of noises. For the salt and pepper noisy image, KGFCM_S obtains the same, and the methods utilizing the median spatial information outperform FCM and GFCM in segmentation performance. Moreover, these kernel methods utilizing the median spatial information obtain better segmentation performance than the other methods. The results obtained using salt and pepper noise with noise factor \([0 \ 0.02]\) are shown in Figure 5.2.
Figure 5.2  Segmentation result of KGFCM_S with salt and peppet noise(0,0.02) for a) test image b) flower c) MRI image1 d) MRI image2

The proposed method segments well the images with more noise with few seconds of additional time. The MRI image with gaussian noise [0 0.02] and salt and pepper noise [0 0.05] are segmented and shown in Figure 5.3 and 5.4.
Figure 5.3  Segmentation with gaussian noise [0 0.02] for a) MRI1 image b) MRI2 image
Figure 5.4  Segmentation with salt and pepper noise [0 0.05] for a) MRI1 image b) MRI2 image

For the salt and pepper noisy images and the methods utilizing the median spatial information outperform FCM and GFCM in segmentation performance. Moreover, these kernel methods utilizing the median spatial information obtain better segmentation performance than the other methods.
The segmentation performances obtained by GKFCM_S are best among all these ten methods. For the mixed noisy image, it attains a little worse segmentation performance than FCM, but consumes less running time. These four methods utilizing the spatial information outperform FCM and GFCM in segmentation performance and convergence speed. Especially, the methods using the median spatial information are more suitable for the image corrupted by the mixed noise than the methods using the mean spatial information.

Generally, incorporating of spatial information into the segmentation process will dramatically increase the algorithm's computational complexity. Table 5.1 provides the time required for segmentation process in test images and medical images. There is a slight difference in time from one image to another and the segmentation depends on the amount of noise in the images. The Gaussian noise with noise factors 0.0125, 0.02 and salt and pepper noise with factors 0.02, 0.05 were considered.

<table>
<thead>
<tr>
<th>Image</th>
<th>Noise type</th>
<th>Noise factor</th>
<th>Time required (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test</td>
<td>Gaussian</td>
<td>0.0125</td>
<td>6</td>
</tr>
<tr>
<td>Flower</td>
<td>Gaussian</td>
<td>0.0125</td>
<td>6</td>
</tr>
<tr>
<td>MR11</td>
<td>Gaussian</td>
<td>0.0125</td>
<td>7</td>
</tr>
<tr>
<td>MR12</td>
<td>Gaussian</td>
<td>0.0125</td>
<td>7</td>
</tr>
<tr>
<td>Test</td>
<td>Salt &amp; pepper</td>
<td>0.02</td>
<td>7</td>
</tr>
<tr>
<td>Flower</td>
<td>Salt &amp; pepper</td>
<td>0.02</td>
<td>7</td>
</tr>
<tr>
<td>MR11</td>
<td>Salt &amp; pepper</td>
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<tr>
<td>MR12</td>
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<td>MR11</td>
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<tr>
<td>MR12</td>
<td>Salt &amp; pepper</td>
<td>0.05</td>
<td>9</td>
</tr>
</tbody>
</table>

Table 5.1 Time required for segmentation in noisy environment
To compare the computational complexity of the FCM, KFCM, GFCM and our GKFCM_S algorithms, we applied each of these four segmentation algorithms to the 256 × 256 MRI image. The comparison graph is shown in Fig. 5.5. The proposed method requires a maximum of 8 seconds while the GFCM requires 25 seconds for the MRI image segmentation.

![Figure 5.5](image1)

**Figure 5.5 Comparison based on time consumption**

The performance of GKFCM_S algorithm is compared with the FCM based algorithms in terms of clustering accuracy with respect to noise factor and shown in Figure 5.6. The proposed GKFCM_S outperforms all the FCM based algorithms with the clustering accuracy of 0.98.

![Figure 5.6](image2)

**Figure 5.6. Comparison based on clustering accuracy**
5.6 CONCLUSION

By introducing the spatial constraint term, the improved GKFCM_S behaves more robust than GFCM in the noisy gray image segmentation. In this modified method, first a term about the spatial constraints derived from the image is introduced into the objective function and then the kernel induced distance is adopted to substitute the Euclidean distance. Experimental results show that the proposed method behaves well for test images, medical images and images corrupted by noise. The test images and medical images corrupted by Gaussian noise, salt and pepper noise have shown that the accuracy of the proposed approach outperforms all the existing FCM methods with the maximum clustering accuracy of 0.98. Further it has been shown that the proposed algorithm segments the images rapidly with less iteration.