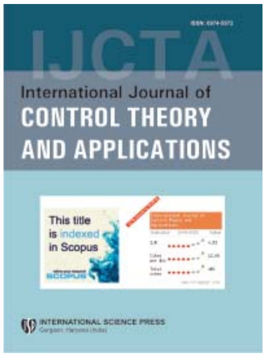

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Design and Implementation of Service Oriented Cloud Computing Architecture for Brain MR Image Segmentation

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Abstract : Managing large image collection has become an important issue for information companies, institutions and Medical Image Analyzer (MIA). In this paper, we introduce our framework Service Oriented Cloud Computing Architecture (SOCCA) design for MR Brain Image segmentation using various hybrid Fuzzy C-Means based on Microsoft technologies and MATLAB NE Builder to overcome various issues that medical image analysis researchers face during their research work such as re-implementing existing methods, developing and deploying new software solutions and the tedious and consuming process to generate ground truth by manually segmenting target shapes. This proposal aims to show the benefits which can be obtained from cloud in order to help the medical image analyzer make better decisions based on the Hybrid Fuzzy C-Means algorithms and proposed clustering algorithm Multiple Kernel Neighborhood Weight Fuzzy C-Means (MKNWFCM). In this research, the quantitative indices are described to extract local features of brain MR Images, when applied on a set of synthetic Brain MR Images, for segmentation. For security and privacy reasons of the algorithms inventors, these algorithms can be hidden in a cloud to allow the users to use the algorithms as a package without any access to see/change their basic code. In another word, in the user part, users can send their images to the cloud and configure the algorithm via an interface.

Keywords: *Service Oriented Cloud Computing Architecture (SOCAA), Multiple Kernel Neighborhood Fuzzy C-Means (MKNWFCM), Magnetic Resonance Brain Image, Cloud services.*

1. INTRODUCTION

Segmentation is a process of partitioning an image space into some nonoverlapping meaningful homogeneous regions. The success of an image analysis system depends on the quality of segmentation [1]. A segmentation method is supposed to find those sets that correspond to distinct anatomical structures or regions of interest in the image. In the analysis of medical images for computer aided diagnosis and therapy, segmentation is often required as a preliminary stage. However, medical image segmentation is a complex and challenging task owing to the intrinsic nature of the images. The brain has a particularly complicated structure and its precise segmentation is very important for detecting tumors, edema and necrotic tissues, in order to prescribe appropriate therapy [2].

Conventionally, brain MR images are interpreted visually and qualitatively by radiologists. Advanced research requires quantitative information such as the size of the brain ventricles after a traumatic brain injury or the relative volume of ventricles to brain. Fully automatic methods sometimes fail, producing incorrect results and requiring the intervention of a human operator. This is often true owing to the restrictions imposed by image acquisition, pathology and biological variation. So, it is important to have a faithful method to measure various structures in the brain. One such method is the segmentation of images to isolate objects and regions of interest.

Segmentation of major brain tissues, including Gray Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CF), from Magnetic Resonance Images (MRI) plays an important role in both clinical practice and neuroscience research. Many image processing techniques have been proposed for MR Image segmentation [3, 4], most thresholding [5, 7], region growing [8], edge detection [9], pixel classification [10, 11] and clustering [12-14]. Some algorithms using the neural network approach have also been investigated in MR image segmentation problems [15, 16].

2. MOTIVATION AND JUSTIFICATION

1. In medical image analysis, a cloud environment can be defined as a framework between users and service providers. However, unifying these resources such as existing algorithms, hardware, images etc in a cloud environment, is an important task which is fraught with a few technical difficulties. Some of the issues are.
2. Medical image analysis researchers spend 30% of their research time on implementing and evaluating existing solutions, which represents a significant amount of time. Further, the development environments of the MIA research of each researcher may vary, leading them to look for software solutions, which are compatible development environments.
3. The development of user interfaces is another challenge for MIA researchers, since the visualization of a user-friendly user interface takes time and effort which an MIA research prefers to invest in proving concepts and learning new programming languages.
4. Another difficulty that MIA researchers face, is obtaining ground truth outlined shapes which are relevant for the validation of image segmentation algorithms. The ground truth images are obtained from either a radiologist or the researcher himself should generate the said image through manual segmentation which is a tedious and time consuming activity.
5. Information sharing is often a sensitive issue, because most researchers are apprehensive about sharing their research or algorithms. They feel threatened if someone else uses their approach or research and hence it is a challenge to obtain cutting edge research methods and compare it with one's own research to develop better framework or algorithms.

But, cloud environment can be a boon to medical image analysis research, since it helps researchers, by unifying all image analysis resources in one environment. Hence, MIA researchers can test their new algorithms, visualize the results and compare with other algorithms by applying on standard ground truth images without spending much time or energy.

In order to achieve this goal, the segmentation algorithms are implemented in cloud environment.

In this paper, the three existing different hybrid fuzzy algorithm namely, Gaussian Kernel Fuzzy C Means [GKFCM] [17], Spatially Constrained Kernel Fuzzy C Means[SFKFCM][18], Multiple Kernel Fuzzy C Means [MKFCM] [19], and Proposed Multiple Kernel Neighbor weighted Fuzzy C-Means (MKNWFCM) are presented for segmentation of Brain MR images as cloud services. Details of proposed algorithm has presented in Section 4.For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

3. CLOUD COMPUTING ARCHITECTURE

Cloud Computing inherited the features of high-performance parallel computing, distributed computing, and grid computing, as well as the further development of these techniques to achieve location transparency to enhance the user experiences over the Internet. Cloud computing is an Internet-based technique using shared resources available remotely. In this computing technique, the internal functions are kept away from the end users. This technique is new to the IT field and is a product where applications are accessed via the Internet. So far, no exact definition for cloud computing is available, however, it can be defined as: 'cloud computing is a type of computing environment, where IT business outsource their computing needs, which include software application services to outside vendors when they are in need of computing power or other resources like storage, database, e-mails, etc., which are accessed via WWW. Cloud computing system can be divided into two parts: front end and back end. The interconnection between them is done via the Internet. Front end is used by the customers and back end refers to the service providers.

The front end contains customer's devices comprising of computers and a network and applications for accessing the back end system, that is, the cloud systems. Front end refers to the interface through which a customer can make use of the services rendered by the cloud computing system. Back end contains physical devices or peripherals. It also contains various computer resources such as CPU and data storage systems. A combination of these resources is termed as cloud computing system. A dedicated server is used for administration purpose. It monitors the consumer's demands, traffics, etc.

4. MULTIPLE KERNEL NEIGHBORHOOD WEIGHTED FUZZY C-MEANS

In a previous research work [20], we presented an evaluation of the performance of various hybrid fuzzy clustering algorithms on brain magnetic resonance images, the experimental results on a set of real and benchmark brain MR images show that the multiple kernel Fuzzy C-Means (MKFCM).

The main advantage of using MKFCM in the proposed technique is that it accepts any kind and any number of kernel functions from multiple heterogeneous or homogeneous sources and thus form a single composite kernel function. For example, from the image itself the intensity of a pixel is gained directly. But the texture information of a pixel might be derived from some wavelet filtering image. Therefore it is necessary to define different kernel functions separately and they are further combined and then we apply the composite kernel in the next phase to get better image segmentation results.

Even though the MKFCM works better and gives efficient segmented results, it still has some disadvantages. The selection of kernel function and the composition of the multiple kernels could change the final results greatly. The kernels used to composite are based on the application which a person chose.

To enhance the Multiple Kernel Fuzzy C-Means, a new method is proposed here by considering the neighborhood weighted pixels in the composite kernel function. In order to unite a kernel for the local spatial information and a kernel for the local spectral information MKFCM is used. But somehow it suffers from the noise pixels in the image. So an enhanced technique is needed here, Multiple Kernel Neighborhood Weighed Fuzzy C Means shortly called as MKNWFCM

The objective function for the proposed technique is

$$J_{\text{MKNWFCM}} = \sum_{i=1}^{c}\sum_{i=1}^{n}\mu_{ij}^{m}(1-K_{\text{com}}(x_i \,.\, a_j)) * Wij$$

In the proposed technique, the combined Gaussian kernel function is formed or single kernel is formed from the composition of multiple kernels in the 1st phase.

Then it is passed to the next step in which the average of the neighboring pixel is replaced with each pixel in the image as a noise removal technique. The neighborhood pixel is chosen based on the pixel distance. Then this average value is multiplied with the kernel image. And this image is used for clustering.

Definition: Neighborhoods [21] given a discrete noisy image X = x_i / $i \in$I, a neighborhood system on I is a family N = $\{N_i\} i \in$ I of subsets of I such that for all $i \in$ I,

1. $i \in N_i$
2. $j \in N_i \Rightarrow i \in N_j$

The subset N_i is called the neighborhood of I, and the subset N_i denotes N_i/i.

The neighborhoods can have different sizes and shapes to better adapt to the image. For simplicity, square windows of fixed size, that is 3 x 3 or 5 x 5 window around the pixel *i* is usually considered. And in the final phase the combined kernel is processed as same as the normal KFCM algorithm. Thus it is named as MKNWFCM – Multiple Kernel Neighborhood Weighted Fuzzy C Means.

4.1. Multiple Kernel Neighborhood Weighted FCM

1. MKNWFCM is an effective technique.
2. Initially create two Gaussian kernel with the size 5 x 5 by using the formula below

$$g(x) = \frac{e^{\frac{-x^2}{2\sigma^2}}}{\sigma\sqrt{2n}}$$

3. Where σ is the smoothing parameter.
4. Then apply these filters on the input image.
5. Find the average of each pixel based on the neighborhood pixel. The neighborhood pixel is chosen based on the pixel distance.
6. Then, this average value is multiplied with the kernel image. And this image is used for clustering using MKFCM technique.

Algorithm

1. Assume

   a) X = $\{x_1, x_2 . . ., x_n\}$, $x_i \varepsilon$ R(s), the data set

   b) $2 \leq c \leq n$, c as the number of clusters

   c) $\varepsilon > 0$, the stopping criterion of algorithm

   d) $a_0(0)$, $a_1(0)$..... $a_{c-1}(0)$the initials of cluster centers

   e) s = 1; σ – standard deviation

   f) Initialize the membership function

   g) Compute the square Euclidean distance measure between the gray levels and the cluster centers as follows

   $$d^2_{x,y} = \|g_x - a_y\|^2 w \text{ for } 1 \leq x \leq n, 1 \leq y \leq c \tag{3}$$

Where,

*i*s the neighborhood based kernel applied image

g is gray level

a is cluster centers

2. Compute the learning rule for the membership function, $\mu_{(s)}$ with cluster centre, $a_{(s-1)}$ using (5)

$$\mu_s(i,j) = \frac{(1-\mathrm{K}_{\mathrm{com}}(x_j,a_i))^{\frac{-1}{m-1}}}{\sum_{k=1}^{c}(1-\mathrm{K}_{\mathrm{com}}(x_j,a_i))^{\frac{-1}{m-1}}},$$
$$i = 1, \ldots, c,$$
$$j = 1, \ldots n \quad (4)$$

3. Update the cluster centers, $a_{(s)}$ with membership function, $\mu_{(s)}$ using (4)

$$a_s(i) = \frac{\sum_{j=1}^{n}\mu_{ij}^{m}(\mathrm{K}_{\mathrm{com}}(x_j,a_i))}{\sum_{j=1}^{n}\mu_{ij}^{m}(\mathrm{K}_{\mathrm{com}}(x_j,a_i))},$$
$$i = 1, \ldots, c,$$
$$j = 1, \ldots n \quad (5)$$

4. Update If $||a_{(s)} - a_{(s-1)}|| < \in$, Stop and output. Else $s = s + 1$ and return to step 2.

5. PROPOSED SERVICE ORIENTED CLOUD COMPUTING ARCHITECTURE(SOCCA)

Fig.2 shows that, in the single cloud site architecture, load balancer, application logic, data-base and storage are located in the cloud, that is, the load balancing server, application server and database server.

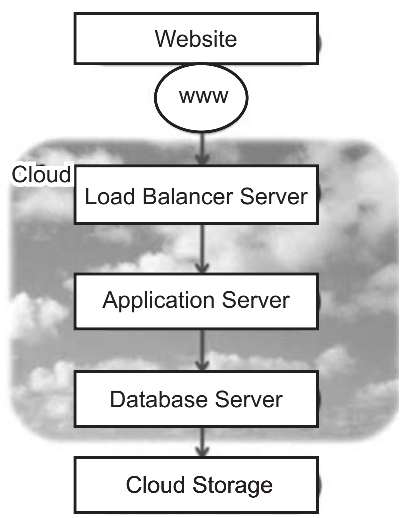


Figure 2: Proposed Service Oriented Cloud Computing Architecture for MR Brain Image Segmentation

5.1. Load Balancing server

Load balancing is dividing the amount of work that a computer has to do between two or more computers so that more work gets done in the same amount of time and, in general, all users get served faster. Load balancing can be implemented with hardware, software, or a combination of both. The load balancing done by the Virtualization Techniques. Typically, load balancing is the main reason for computer server clustering. In this implementation, we use System Center Virtual Machine Manager R2 + SP1 and SCVMM Self service portal 2.0 for diving the work, and assigning into the various virtual machines. It is also useful in monitoring, reporting, change management, deployment and more.

5.2. Application Server

An application server is a server program in a computer in a distributed network that provides the business logic for an application program. The application server contains various hybrid Fuzzy C-Means Algorithms. These algorithms are implemented in MATLAB and which are connected with ASP.Net using MATLAB NE Builder.

5.3. Database Server

A database server can be defined as a server dedicated to providing database services. Such a server runs the database software. It contains User's detail, Meta data such as simulated MR Brain Image data set, and Self-service portal 2.0 details.

6. CLOUD DESIGN FOR MEDICAL IMAGE ANALYZER

Fig.3 shows that, in the single cloud site architecture, load balancer, application logic, data-base and storage are located in the cloud, that is, the load balancing server, application server and database server.

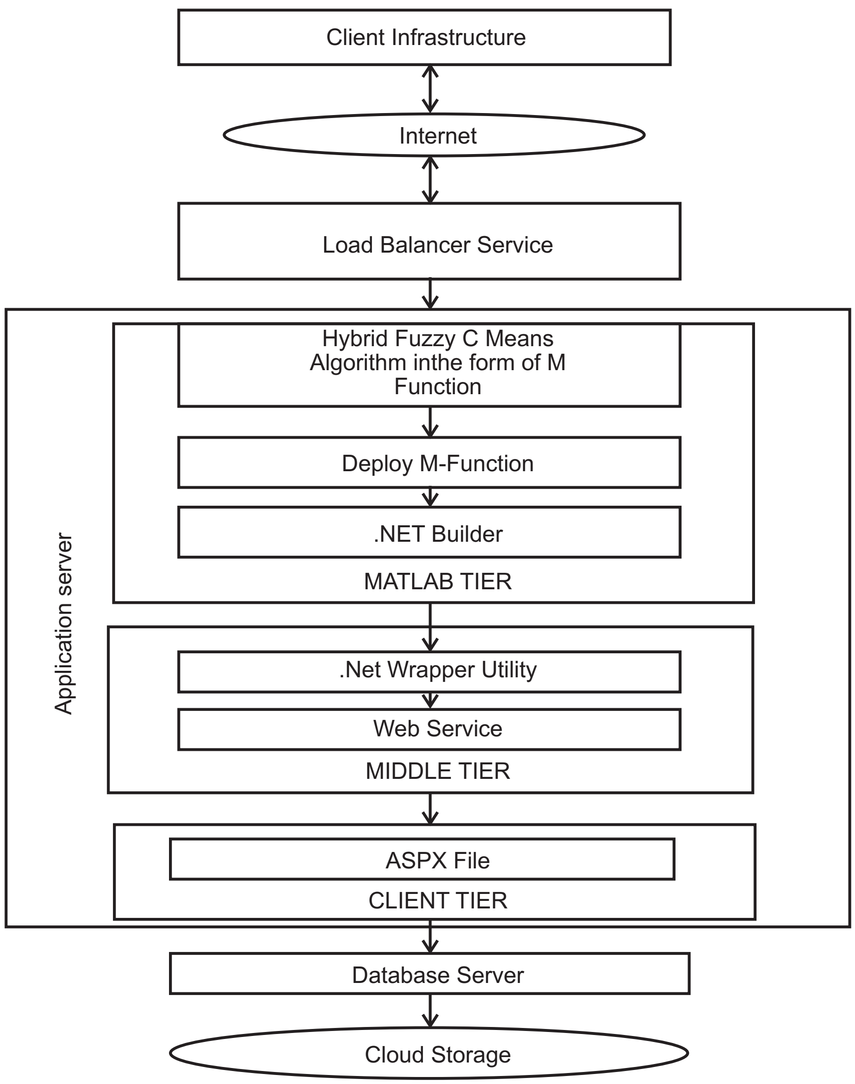


Figure 3: Architecture of Proving Hybrid Fuzzy C-Means Algorithm as a Cloud Service

The proposed method consists of two main modules, namely 1) User interface 2) The processing unit. The MRI process can be transmitted and stored in a remote server, which performs the segmentation and returns the results and also makes the MRI process and the automatic segmentation services available on the server. For each module, the most suitable technology has been decided a priori: ASP.Net for the user interface and MATLAB NE builder for the processing unit. ASP.NET is a set of web application development technologies marketed by Microsoft Programmers can use it to build dynamic web sites, web applications and XML web services. It is part of Microsoft's .NET platform and is the successor to Microsoft's Active Server Pages (ASP) technology.

MATLAB Builder NE can create .NET and COM components from MATLAB programs that include MATLAB math and graphics and GUIs developed with MATLAB. we can integrate these components into larger .NET, COM, and Web applications and deploy them royalty-free to computers that do not have MATLAB installed using the MATLAB compiler Runtime (MCR) that is provided with MATLAB Compiler. Using MATLAB Compiler, MATLAB Builder NE encrypts our MATLAB programs and then generates .NET or COM wrappers around them, so that they can be accessed just like native .NET and COM components.

Fig.3 Allows a platform to have an independent access to remote computing service, its cloud services allow end users to fully interact with data, information requests as well as applications with a low level of user interaction. We develop our framework which shows a few user interactions are required with a very simple graphic user interface. Images can be uploaded by user disk, then click the submit button. The proposed architecture solves the incompatibility problems because it transfers the processing load to the server, and end users can access the application without installing MATLAB or the Matlab Compiler Runtime (MCR) on their individual computers. For instance, we will use visual studio as our development environment, SQL server as our database manager, and Microsoft Workflow foundation as our workflow engine, which is part of the Microsoft .NET Framework 3.0.

7. IMAGE SEGMENTATION QUALITY MEASURES

In supervised approaches to segmentation and classification routines, definition of segmentation quality by measures such as accuracy and precision is quite straightforward by means of ground-truth ideal images. On the other hand, during clustering routines, this kind of indispensable segmentation quality assessment is not always feasible because ground-truth image is not present or is difficult to obtain. In the present study, the following segmentation quality measures were taken into account as cluster validity indices. Data clustering as data grouping routine (together with other grouping algorithms such as data thresholding) presents unsupervised process that finally requires some sort of quality evaluation of generated data groups or clusters. This requirement can be satisfied by using cluster validity indices. In general, three distinctive approaches to cluster validity are possible. The first approach relies on external criteria that investigate the existence of some predefined structure in clustered data set. The second approach makes use of internal criteria and the clustering results are evaluated by quantities describing the data set such as proximity matrix etc. Approaches based on internal and external criteria make use of statistical tests and their disadvantage is high computational cost. The third approach makes use of relative criteria and relies on finding the best clustering scheme that meets certain assumptions and requires predefined input parameters values. Most commonly used indices are Dunn index, Davis-Bouldin index, and β-Index.

7.1. Cluster Validity Quantitative Measure

7.1.1. Davis-Bouldin Index [22]

The Davis-Bouldin index minimizes the average similarity between each cluster. It is defined as the ratio of the sum of within-cluster scatter to between-cluster separation. The objective is to minimize this index. The Davis-Bouldin index is defined as follows:

$$DB = \frac{1}{k}\sum_{i=1}^{k} \max_{j=1,\ldots,k,\, i\neq j}\left(\frac{\mathrm{diam}(C_i)+\mathrm{diam}(C_j)}{d(C_j, C_j)}\right) \tag{6}$$

Where $d(u, w)$ represents the Euclidean distance between u and w and diam(C) is the diameter of a cluster which can be defined as

$$\mathrm{diam}(C) = \max_{u,\, \omega C} d(u, w) \tag{7}$$

7.1.2. Dunn Index [23]

The Dunn index is a well known validity index, proposed by () that recognizes compact and well separated clusters by means of considering five different measures of distance between clusters and three different measures of cluster diameter. The value of the Dunn index should be maximized and is defined in the following way

$$D = \min_{i=1,\ldots,k}\left\{\min_{j=i+1,\ldots k} \frac{\mathrm{dist}(C_i, C_j)}{\max_{a=1,\ldots,i} \mathrm{diam}(C_a)}\right\} \tag{8}$$

Where dist(C_k,C_ p) represents the dissimilarity function between two clusters C_k and C_p calculated as

$$\mathrm{dist}(C_k, C_p) = \min_{\mu \in C_k,\, \omega \in C_p} d(u, v) \tag{9}$$

7.1.3. β-Index [21]

The β – index measures the ratio of the total variation and within-class variation. Define *n_i* as the number of objects in the ith (i = 1,…,k) cluster from segmented image. Define X_*ij* as the value of *jth* data object (j = 1,…, *n_i*) in the cluster i and (X_*i*)¯the mean of *n_i* values of the *i-th* cluster. The β–index is defined in the following way

$$\beta - \text{index} = \frac{\sum_{i=1}^{k} \sum_{j=1}^{n_j} (X_{ij} - \overline{X})^2}{\sum_{i=1}^{k} \sum_{j=1}^{n_i} (X_{ij} - \overline{X}_1)^2} \tag{10}$$

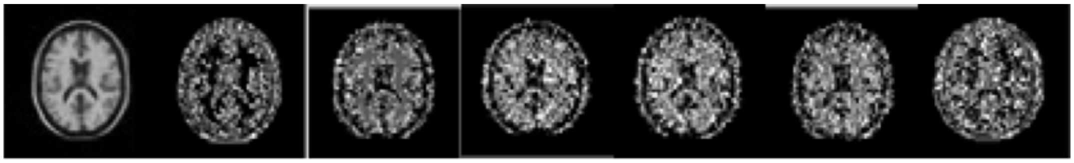
Where (X)¯represents the mean value of all universe objects attributes. This index defines the ratio of the total variation and the within-class variation. In this context, important notice is the fact that β–index value increases as the increase of k number of cluster centers.

8. PERFORMANCE OF SIMULATED BRAIN MR IMAGES

Extensive experimentation is done to evaluate the performance of the MKNWFCM algorithm on simulated Brain MR Images obtained from BrainWeb: Simulated Brain Database [25].

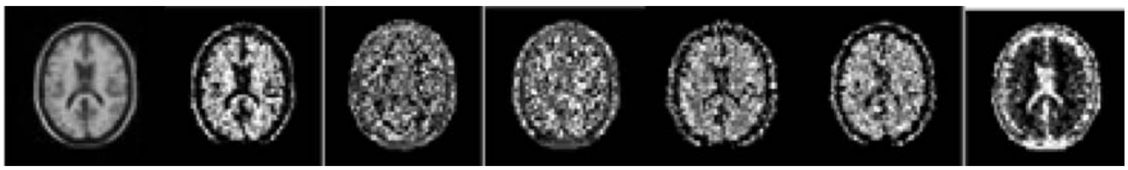
(*a*) (*b*) (*c*) (*d*) (*e*) (*f*) (*g*)

Figure 4: Slice thickness = 1 mm: original and segmented versions of MKNWFCM algorithm for different noise evels. (*a*) Original (*b*) noise = 0%, (*c*) noise = 1% (*d*) noise = 3% (*e*) noise = 5% (*f*) noise = 7% and (*g*) noise = 9%



(*a*) (*b*) (*c*) (*d*) (*e*) (*f*) (*g*)

Figure 5: Slice thickness = 3 mm: original and segmented versions of MKFCM algorithm for different noise levels. (*a*) Original (*b*) noise = 0%, (*c*) noise = 1% (*d*) noise = 3% (*e*) noise = 5% (*f*) noise = 7% and (*g*) noise = 9%



(*a*) (*b*) (*c*) (*d*) (*e*) (*f*) (*g*)

Figure 6: Slice thickness = 5 mm: original and segmented versions of MKFCM algorithm for different noise levels. (*a*) Original (*b*) noise = 0%, (*c*) noise = 1% (*d*) noise = 3% (*e*) noise = 5% (*f*) noise = 7% and (*g*) noise = 9%

Fig. 4, 5 and 6 present the original and segmented images obtained using the MKNWFCM algorithm for different slice thickness and noise levels. The results are reported for three different slice thicknesses: 1, 3, and 5 mm, and the noise various from 0 to 9%. The noise is calculated relative to the brightest tissue. Finally, Tables 1, 2, and 3 compare the values of DB, Dunn, and indices of different *c*-means algorithms for different slice thickness and noise levels. All the results reported in Fig.4,5 and 6 and Tables 1, 2, and 3 confirm that the MKNWFCM algorithm generated good segmented images irrespective of the slice thickness and noise level. Also, the performance of the MKNWFCM algorithm in terms of DB, Dunn, and indices is significantly better compared to other hybrid fuzzy C-means algorithms.

Table 1
Value of DB Index for Simulated Brain MRI

Slice Thickness	*Algorithms*	*Noise (%)*				
		0	*1*	*3*	*5*	*7*
1	GKFCM	3.35	3.97	4.06	4.78	4.41
	SCFKFCM	5.25	4.18	4.64	3.25	4.00
	MKFCM	3.11	4.73	3.68	4.59	4.20
	MKNWFCM	3.08	4.43	3.57	4.42	4.12
3	GKFCM	4.74	4.08	5.77	5.64	3.99
	SCFKFCM	3.78	4.30	3.57	3.79	3.07
	MKFCM	3.43	3.68	4.94	4.33	3.63
	MKNWFCM	3.25	3.47	4.43	4.21	3.54
5	GKFCM	5.32	6.81	4.82	4.50	5.45
	SCFKFCM	2.98	3.56	2.80	2.47	3.12
	MKFCM	4.61	5.94	4.56	4.20	3.05
	MKNWFCM	4.32	5.54	4.45	4.13	3.01

Table 2
Value of Dunn Index for Simulated Brain MRI

Slice Thickness	*Algorithms*	*Noise (%)*				
		0	*1*	*3*	*5*	*7*
1	GKFCM	1.42	1.48	1.48	1.34	1.38
	SCFKFCM	1.44	1.39	1.29	1.44	1.49
	MKFCM	1.15	1.49	1.45	1.45	1.38
	MKNWFCM	1.13	1.35	1.39	1.44	1.28
3	GKFCM	1.26	1.45	1.25	1.36	1.43
	SCFKFCM	1.43	1.34	1.25	1.42	1.25
	MKFCM	1.26	1.36	1.25	1.47	1.37
	MKNWFCM	1.13	1.23	1.21	1.34	1.26
5	GKFCM	1.29	1.39	1.68	1.60	1.57
	SCFKFCM	1.29	1.39	1.54	1.55	1.50
	MKFCM	1.29	1.38	1.68	1.55	1.57
	MKNWFCM	1.28	1.35	1.63	1.43	1.34

Table 3
Value of Index for Simulated Brain MRI

Slice Thickness	*Algorithms*	*Noise (%)*				
		0	*1*	*3*	*5*	*7*
1	GKFCM	5.34	5.43	5.43	4.87	4.73
	SCFKFCM	5.34	5.43	5.43	4.87	4.73
	MKFCM	0.21	0.22	0.20	0.19	0.19
	MKNWFCM	0.18	0.19	0.23	0.21	0.24
3	GKFCM	5.37	5.36	5.20	4.94	4.95
	SCFKFCM	5.37	5.36	5.20	4.94	4.95
	MKFCM	0.22	0.21	0.20	0.20	0.20
	MKNWFCM	0.18	0.19	0.21	0.22	0.18
5	GKFCM	5.42	5.26	4.91	4.76	4.51
	SCFKFCM	5.42	5.26	4.91	4.76	4.51
	MKFCM	0.22	0.21	0.20	0.19	0.18
	MKNWFCM	0.21	0.18	0.19	0.18	0.18

9. CONCLUSION AND DISCUSSION

In this paper, we have presented a cloud service for image segmentation algorithms that focuses on the challenges and problems posed by very large datasets. It has been implemented using Microsoft Technologies and MATLAB NE Builder for very large datasets in cloud environment. In terms of performances, the Cloud Environment was faster than the web Environment. A Cloud service reduces the time and the computing power for image segmentation algorithms. The computational results show that the MKNWFCM provides better result compared to the other three segmentation algorithms. Our system is implemented based on SOCCA technology for consideration of the consistency, security and interoperability of cloud services.

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