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ADVANCED CLUSTER BASED IMAGE SEGMENTATION

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Abstract
This paper presents efficient and portable implementations of a useful image segmentation technique which makes use of the faster and a variant of the conventional connected components algorithm which we call parallel Components. In the Modern world majority of the doctors are need image segmentation as the service for various purposes and also they expect this system is run faster and secure. Usually Image segmentation Algorithms are not working faster. In spite of several ongoing researches in Conventional Segmentation and its Algorithms might not be able to run faster. So we propose a cluster computing environment for parallel image Segmentation to provide faster result. This paper is the real time implementation of Distributed Image Segmentation in Clustering of Nodes. We demonstrate the effectiveness and feasibility of our method on a set of Medical CT Scan Images. Our general framework is a single address space, distributed memory programming model. We use efficient techniques for distributing and coalescing data as well as efficient combinations of task and data parallelism. The image segmentation algorithm makes use of an efficient cluster process which uses a novel approach for parallel merging. Our experimental results are consistent with the theoretical analysis and practical results. It provides the faster execution time for segmentation, when compared with Conventional method. Our test data is different CT scan images from the Medical database. More efficient implementations of Image Segmentation will likely result in even faster execution times.

Keywords:
Parallel Algorithms, Region Growing, Image Enhancement, Image Segmentation, Parallel Performance

1. INTRODUCTION

Image segmentation is one of the most important precursors for Image Processing-based applications and has a decisive impact on the overall performance of the developed system. Typically, the goal of image segmentation is to locate certain objects of interest in an image. Image Segmentation is the technique of decomposing an image into meaningful parts, or objects. It results in a segmented image, where each object is labeled in a way that facilitates the description of the original image so that it can be interpreted by the system that handles the image.

One important area of research is to perform image segmentation to evaluate the similarity of the regions which is used to automatically segment the images into meaningful parts. Image Segmentation is a fundamental process in digital image processing which consists of many application areas such as Medical Image Computing, Remote Sensing, Face recognition, etc . The main purpose of image segmentation is to extract the regions of similar interest which is used for subsequent processing that includes object representation and description.

Clustering [8][9][5] is a process in which observed data or entities are grouped together to form a number of clusters in such a way that the entities within a cluster are more similar to each other than those in other clusters. The objects are thereby organized into an efficient representation that characterizes the population being sampled. Various clustering procedures[2] have been developed for such diverse fields as Statistical data analysis, Medical Imaging and Pattern Recognition[24].

2. ARCHITECTURAL DESIGN

Design is basically a bridge between analysis and implementation phases. It illustrates how to achieve the solution domain from the problem domain. The main objective of the design is to transform the high level analysis concepts, used to describe problem domain, into an implementation form. Architectural design is concerned with refining the conceptual view of the system, identifying internal processing functions, decomposing high level functions into sub-functions.

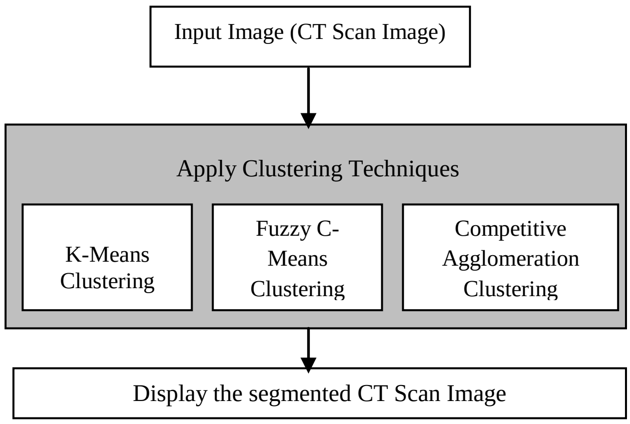


Fig.1. Conventional Architectural Design

Fig.1 describes the detailed architecture of Conventional mode design of three standard methods of segmentation

The standard clustering techniques are applied on the CT scan images of the brain[27][30] in order to investigate which techniques returns the most consistent result based on evaluating the performance of the clustering techniques. The segmentation process is handled out by applying three standard clustering techniques such as K-Means[18], Fuzzy C-Means[4], and Competitive Agglomeration Clustering[28]. Hence the segmented part of the CT Scan[11][14][15] is located by applying these clustering techniques.

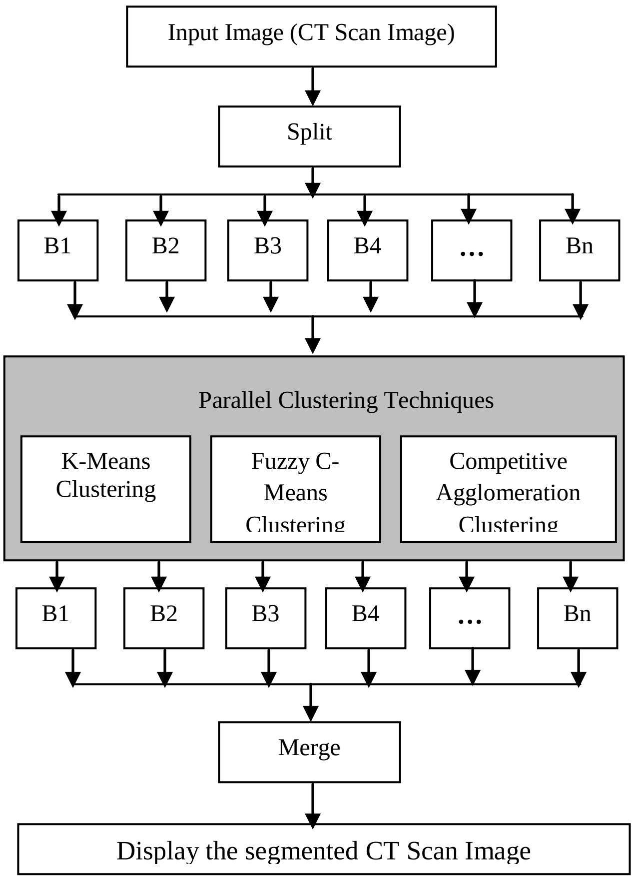


Fig.2. Parallel Architectural Design

Fig.2 describes the detailed architecture of parallel mode design[35][10] of three standard methods of segmentation such as K-Means, Fuzzy C-Means, and Competitive Agglomeration Clustering.

3. CLUSTERING TECHNIQUES

Clustering is a technology that is being used in many technologies that are emerging today. Clustering basically means grouping of objects into different groups based upon some common characteristics[5].

The members of a cluster can't be defined very precisely as there are many ways to represent a cluster[13]. The members are formed only based upon the way the cluster is defined. For example, at times the cluster might be defined very distinctively so that every member falls into a specific group. At other times the cluster may be overlapping with each other, thus making one member to fall in more than one group. There are still more ways to represent a cluster[25].

Three standard clustering techniques used for the purpose of image segmentation are

1. K-Means Clustering,
2. Fuzzy C-Means Clustering
3. Competitive Agglomeration Clustering.

3.1 K-MEANS CLUSTERING

K-Means clustering is a non-hierarchical technique that follows a simple and easy way to classify a given dataset through a certain number of clusters. It is a non-fuzzy clustering method whereby each pattern can only belong to one cluster at any one time[32].

The aim of the K-Means is the minimization of an objective function:

$$J(V)=\sum_{i=1}^{c}\sum_{j=1}^{c_1}\left\|x_{ij}-v_j\right\|^2 \tag{1}$$

where $\| x_{ij} - v_j \|$ is the Euclidean distance between a data point x_{ij} and the cluster center v_i. Centroids are computed as the mean of all points in group i:

$$v_i=\frac{1}{c_i}\sum_{j=1}^{c_1}x_{ij} \quad \text{i=1....c} \tag{2}$$

where, c_i is the number of data points in the cluster i.

The methodology used for implementing the K-Means clustering is described as follows:

1. Read the CT scan brain image as input.
2. Convert the image into data type double.
3. Define the number of clusters 'n' .
4. Call the built in function 'kmeans' by passing number of clusters 'n' and input image as the arguments.
5. Declare 'result image' as the zeros matrix for the size of image (256 x 256).
6. Get the clustered image and store it in the variable 'result image'.
7. Display the resultant image using imshow method.

The center of a cluster is called as the centroid. Each point is assigned to a cluster based upon its nearness to the centroid of the cluster[13]. The centroid is a mean of all varying dimensions assigned to a cluster. The K-means algorithm takes care of this responsibility.

3.2 FUZZY C-MEANS CLUSTERING

Fuzzy clustering is a method to get "natural groups" in the given observations using an assumption of a fuzzy subset on clusters. The fuzzy set theory allows an element of the data to belong to a cluster with a degree of membership that has a value in the interval [0, 1]. The most known method of fuzzy clustering is the Fuzzy C-Means[31] method (FCM).

The membership grades of an entity decides the degree of the entity to which it belongs in a cluster in fuzzy set theory. Fuzzy c-means tries to imitate K-means in minimizing the following function[8].

$$J=\sum_{i=1}^{c}\sum_{j=1}^{c_1}(u_{ij})^m\left\|x_{ij}-v_j\right\|^2 \tag{3}$$

where, u_{ij} is the membership degree of data xi to the cluster center v_j. The parameter m is called the fuzzifier factor and determines the level of cluster fuzziness. The objective of the Fuzzy C-Means algorithm is the minimization of the intra-cluster variability.

Each point is assigned a degree of belonging to a cluster in Fuzzy clustering. This degree determines the belonging of a point to multiple cluster rather than one cluster completely. For example the degree of belonging to a K^{th} cluster can be determined as Uk(x). The summation of the degrees of a point in all clusters is defined as 1. In fuzzy c-means the the mean of degree of all points weighted against belonging to a cluster forms the centroid. The distance of the cluster is inversely proportional to the degree of belonging[13]. Then a real parameter m>1 is used to conventionalize and fuzzify so that the sum equals 1.

The methodology used for implementing the Fuzzy C-Means clustering is described as follows:

1. Read the CT scan brain image as input.
2. Convert the image into data type double.
3. Define the number of clusters 'n'.
4. Reshape the input image into linear array to give as an argument for the fcm built-in function.
5. Call the built in function 'fcm' by passing number of clusters 'n' and reshaped image as the arguments.
6. Get the clustered image and store it in the variable 'segmented image'.
7. Display the resultant image using imshow method.

The FCM tries to move the cluster centers to the right location by consistently updating the centre of the clusters. But it does not take care if the center lies in the correct location. The initial selection of the location finalizes the performance[20]. The main advantage is that clusters with overlapping tendencies can obtain partial membership in individual clusters.

3.3 COMPETITIVE AGGLOMERATION CLUSTERING

The Competitive Agglomeration clustering algorithm is an enhanced Fuzzy C-Means algorithm. The data obtained is classified into different cluster sets using a competitive fuzzy clustering algorithm called Competitive Agglomeration[4][7].

The Competitive Agglomeration algorithm uses the survival of the fittest mechanism for efficient functioning[19]. It starts with a huge number of clusters which compete for feature points. During the process only those clusters that have high cardinality will survive and the other clusters are removed from the scenario[28][17]. This finally will produce optimal number of clusters when the fuzzy based function is minimized.

There are a lot of methods that can be used for segmentation in images. The Competitive Agglomeration is one among the widely used methods. The minimization of the following prototype-based object function is done by the Competitive Agglomeration Algorithm (CA) which searches the optimal cluster prototypes for finishing the work[28].

$$J=\sum_{i=1}^{M}\sum_{j=1}^{N}u_{ij}^{2}d^{2}(z_j,v_i)-\alpha\sum_{i=1}^{M}\left[\sum_{j=1}^{N}u_{ij}\right]^{2} \text{ and } \sum_{i=1}^{M}u_{ij}=1 \quad (4)$$

$$\alpha(k)=\eta_0\exp\left(-k/\tau\right)\frac{\sum_{j=1}^{c}\sum_{i=1}^{n}\left(u_{ji}\right)^{2}d^{2}\left(x_i,c_j\right)}{\sum_{j=1}^{c}\left[\sum_{i=1}^{n}\left(u_{ji}\right)\right]^{2}} \quad (5)$$

where, $\eta_0\ \exp(-k/\tau)$ is the exponential factor, η_0 is the initial value and k is the number of iterations.

Eq.(4) has two major components that needs notice. The first component resembles the fuzzy C-means objective function and performs the same work. The sum of squares of the cardinalities of the cluster can be represented by the second component[9].

The methodology used for implementing the Competitive Agglomeration clustering is described as follows:

1. Read the CT scan brain image as input.
2. Convert the image into data type double.
3. Define the number of clusters 'n'.
4. Generate initial fuzzy partition matrix for fuzzy C-means clustering.
5. The summation of each column of the generated U is equal to unity, as required by fuzzy C-means clustering.
6. Compute the initial cardinality and store it in variable 'center'.
7. Loop in the following steps until the required criterion is met.
8. Compute the distance d2(xi, cj) between data points and the cluster center.
9. Calculate α(k) using the eq.(5)
10. Discard the clusters if the cardinality is less than the error tolerance value.
11. Update the number of clusters by decrementing 1 and increment the iteration counter by 1.
12. Display the resultant image using imshow[12] method.

4. CLUSTERING ENVIRONMENT

In our proposed Image Segmentation Scheme, all the free processors are grouped to form a Cluster Environment based on Master Node. Depending on the Modern Distribution Scheme (MDS) the job is to be divided, processed and merged to produce the final result.

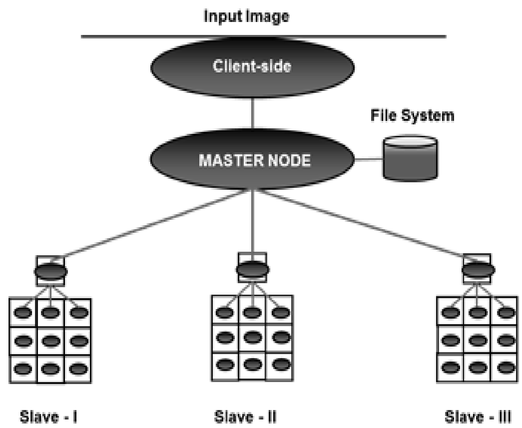


Fig.3. Java Clustering Enviroment

Fig.3 shows that the Java Clustering Environment having group of nodes and an Master Node. It Addtionaly having an file System for Iamge Storage[16] [19][12][3][1][6].

5. SYSTEM DESIGN

5.1 OVERALL DESIGN

The overall System named as Secure[15][29] and Faster Segmentation Engine [SFCE], it consists of Two Major Process for Satisfy its main goal such as Security, Speed, Accuracy, Scalability and Reliability[20].

Two Major processes involved in this scheme. The Processes are

- Modern Distribution Scheme (MDS)
- Safe Cluster Grouping (SCG)

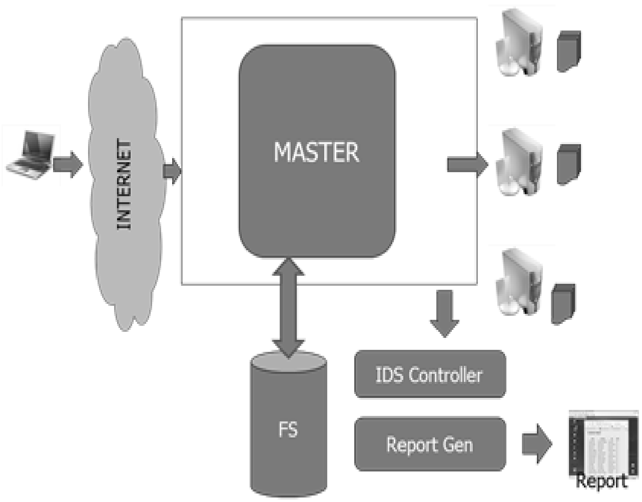


Fig.4. Architecture of Secure and Faster Segmentation Engine [SFCE]

Fig.4 Describes the Architecture of Secure and Faster Segmentation Engine [SFCE] and its main the models such as Modern Distribution Scheme (MDS), Safe Cluster Grouping (SCG).

5.2 MODERN DISTRIBUTION SCHEME (MDS)

Based on the following algorithm, the Process will run on the server.

Check The Number of Processors Available in Cluster and Find its 2^n Value negate remaining based on priority
If 2^n is fit then
    If Check Availability of Matlab and Alg Then
        Splits Image into 2^n pieces
        Perform Image Compression
            using 2^n Nodes in secure way
        Merges 2^n pieces into Output Image
    End
End

Algorithm Modern Distribution Scheme

Algorithm 1 describes the Modern Distribution Scheme for faster processing

This Cluster Algorithm is used to perform faster cluster processing in our domain.

5.3 SAFE CLUSTER GROUPING (SCG)

Based on the following algorithm, the Process will run on the server.

Begin
Establish Connection
Create a Cluster Server for Master
2^n Slave Client Nodes
If a Authorized trigger signal send to client
    it reads a file from File System
    Perform Fast Image Compression
    Writes the file to File System
else
        Wait for Connection
End
End

Algorithm Safe Cluster Grouping Scheme

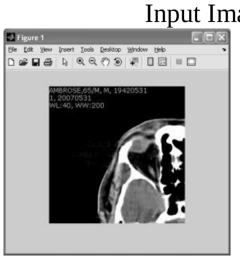
Algorithm 2 describes the Safe Cluster Grouping Scheme for secure processing.

6. EXPERIMENTAL RESULTS

The experimental results are shown below:

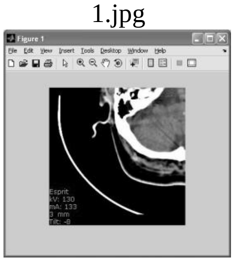
Example: K-Means Method

Input Image: image0.jpg

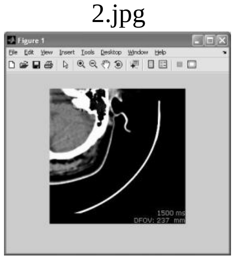


1.jpg

2.jpg



3.jpg

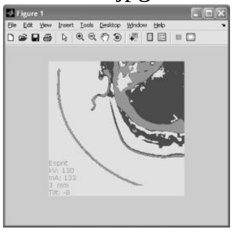


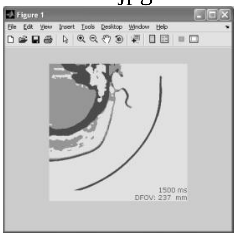
4.jpg

Splited Image for Parallel Processing (before parallel Segmentation process)


b1.jpg


b2.jpg


b3.jpg


b4.jpg

Splited Image for Parallel Processing (After parallel Segmentation process)

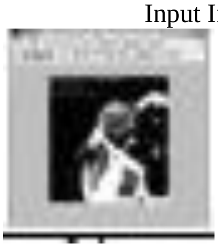

Output Image : Final.jpg

Fig.5. K-Means Method

Fig.5 describes the K-Means method of cluster computing Process for faster and secure processing.

Example : Fuzzy C Mean Method


Input Image: image1.jpg


1.jpg


2.jpg


3.jpg


4.jpg

Splited Image for Parallel Processing (before parallel Segmentation process)


b1.jpg


b2.jpg


b3.jpg


b4.jpg

Splited Image for Parallel Processing (After parallel Segmentation process)

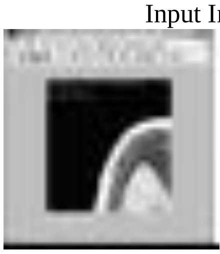

Output Image : Final.jpg

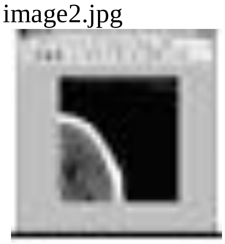
Fig.6. Fuzzy C Means Method

Fig.6 describes the Fuzzy C Means method of cluster computing process for faster and secure processing.

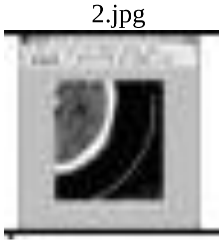
Example : Agglomeration Method


Input Image: image2.jpg


1.jpg


2.jpg

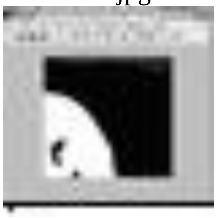

3.jpg


4.jpg

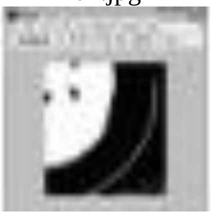
Splited Image for Parallel Processing (before parallel Segmentation process)

b1.jpg

b2.jpg

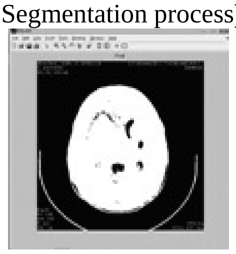


b3.jpg



b4.jpg

Splited Image for Parallel Processing (After parallel Segmentation process)



Output Image : Final.jpg

Fig.7. Agglomeration Method

Fig.7 describes the Agglomeration method of cluster computing Process for faster and secure processing.

7. COMPARATIVE RESULTS

Conventional and Cluster processes are tested for 10 sample images and its comparative results are displayed in the graphical representation below. From this, we found that performance of cluster process is better than conventional process.

Image-Time taken for Normal Vs Cluster Segmentation Process in Milli Seconds

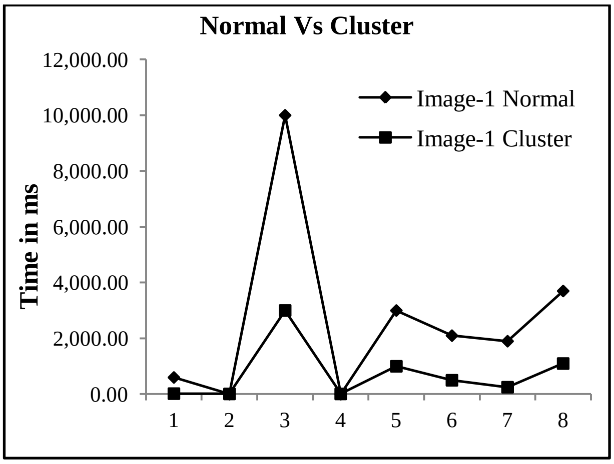


Image 1

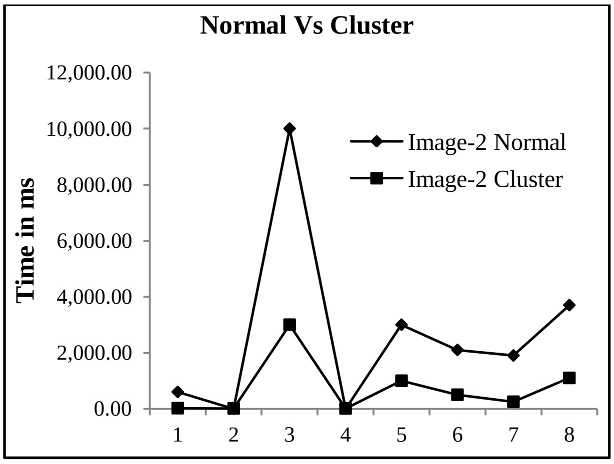


Image 2

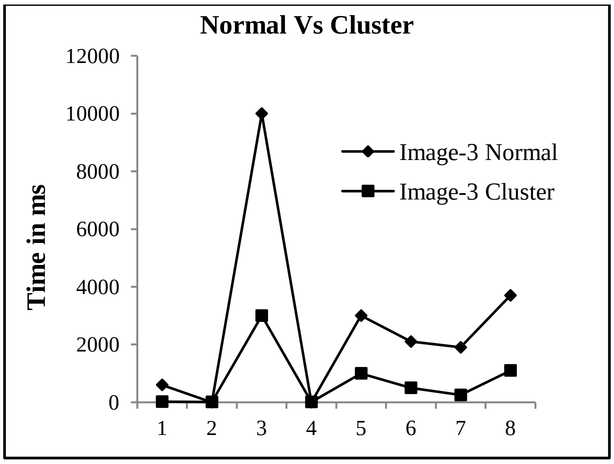


Image 3

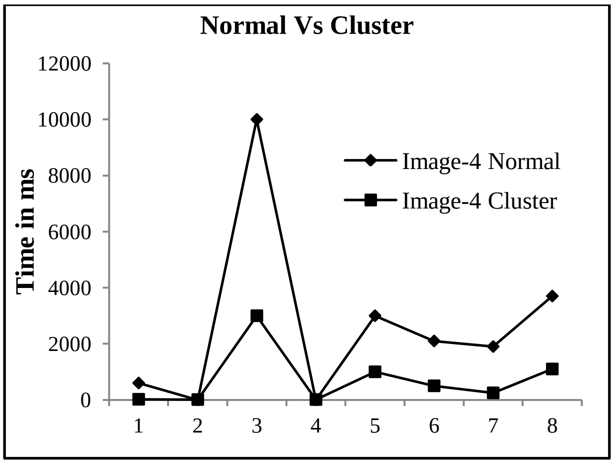


Image 4

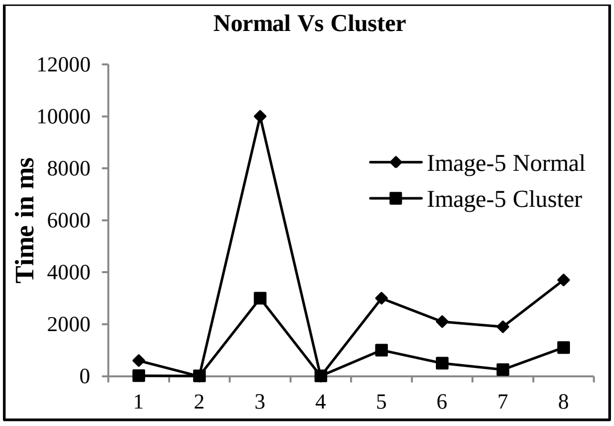


Image 5

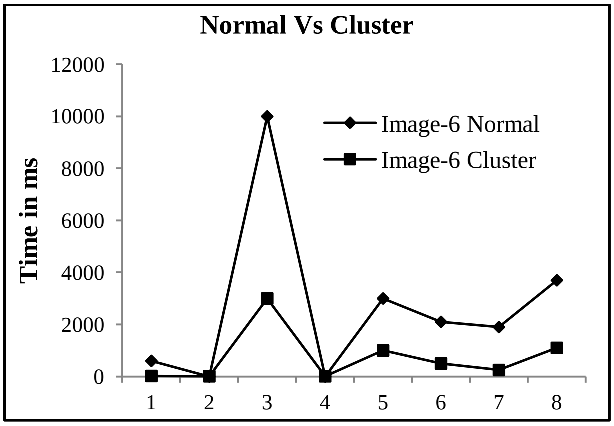


Image 6

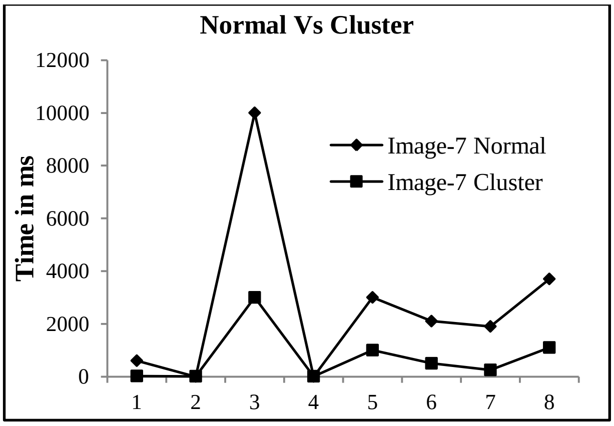


Image 7

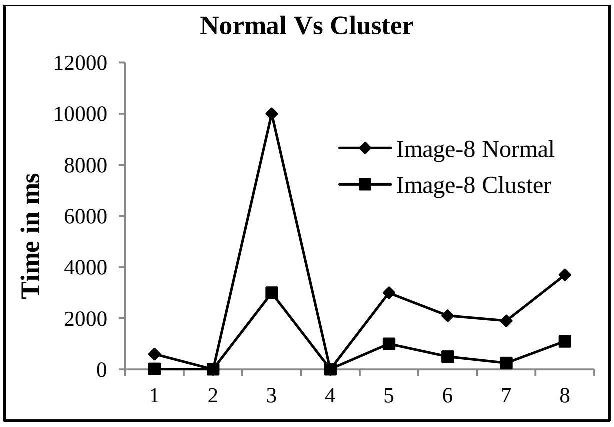


Image 8

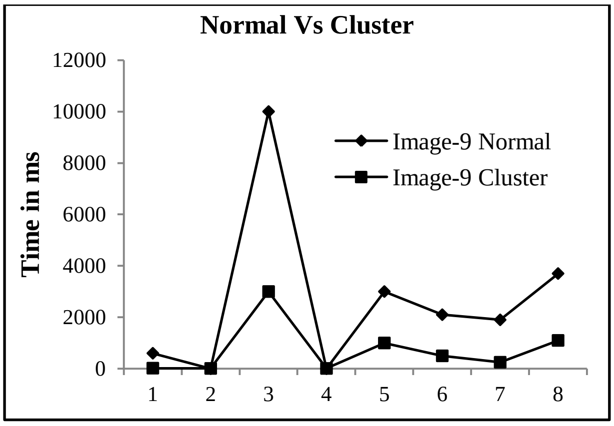


Image 9

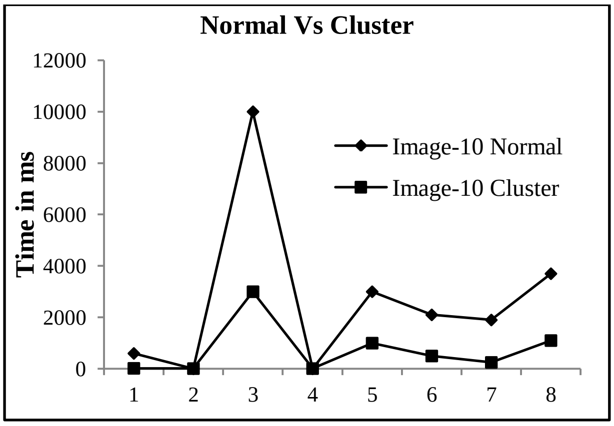
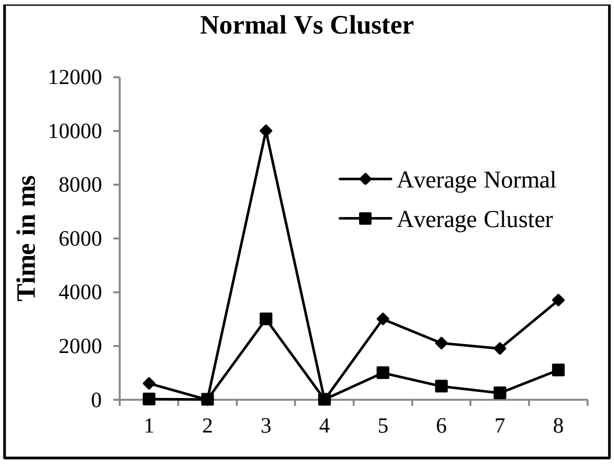


Image 10



Average of 10 images

Fig.8. Conventional Vs Cluster Method of competitive agglomeration clustering

Fig.8 describes the detailed higher time difference of conventional and cluster methods.

8. PERFORMANCE EVALUATION

Table.1. Single Node - Conventional Vs Cluster Methods

Sl. No.	Process (Time taken)	Conventional Methods (ms)			Cluster Methods (ms)		
		K-Means	Fuzzy C-Means	Competitive Agglomeration	K-Means	Fuzzy C-Means	Competitive Agglomeration
1	Split Operation	223.46	223.46	223.46	223.46	223.46	223.46
2	Segmentation (Block-I,II,III,IV) Operation	260.56	295.05	483.49	60.86	69.76	123.86
3	Merge Operation (Seconds)	153.96	153.96	153.96	149.96	149.96	149.96
4	Show Operation (Seconds)	156.95	156.95	156.95	154.95	154.95	154.95
	Total Time	794.93	829.42	1017.86	589.23	598.13	652.23

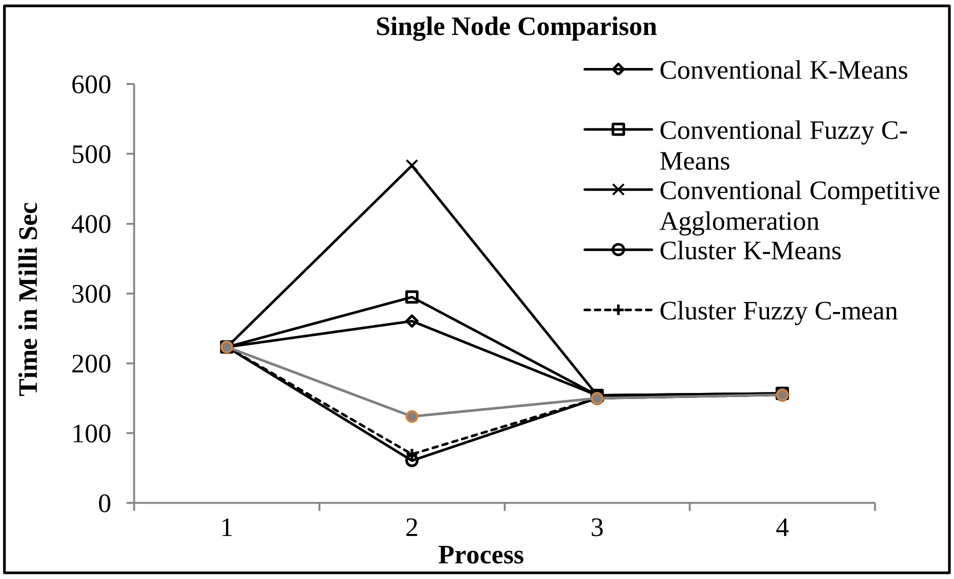


Fig.9. Single Node - Conventional Vs Cluster Method

Table.1 Single Node - Conventional Vs Cluster Method and Fig.9 describes the Single Node - Conventional Vs Cluster Method for faster and secure processing.

Table.2. Four Nodes - Conventional Vs Cluster Method

Sl. No.	Process (Time taken)	Conventional Methods (ms)			Cluster Methods (ms)		
		K-Means	Fuzzy C-Means	Competitive Agglomeration	K-Means	Fuzzy C-Means	Competitive Agglomeration
1	Split Operation	223.46	223.46	223.46	223.46	223.46	223.46
2	Segmentation (Block-I) Operation	60.08	70.90	127.86	50.32	68	70.82
3	Segmentation (Block-II) Operation	65.09	71.2	117.83	-	-	-
4	Segmentation (Block-III) Operation	66.08	73	112.96	-	-	-
5	Segmentation (Block-IV)	64	70.08	114.81	-	-	-

	Operation						
6	Merge Operation (Seconds)	145.96	145.96	145.96	145.96	145.96	145.96
7	Show Operation (Seconds)	157.92	157.92	157.92	157.92	157.92	157.92
	Total Time	782.59	812.52	1000.8	577.66	548.98	598.16

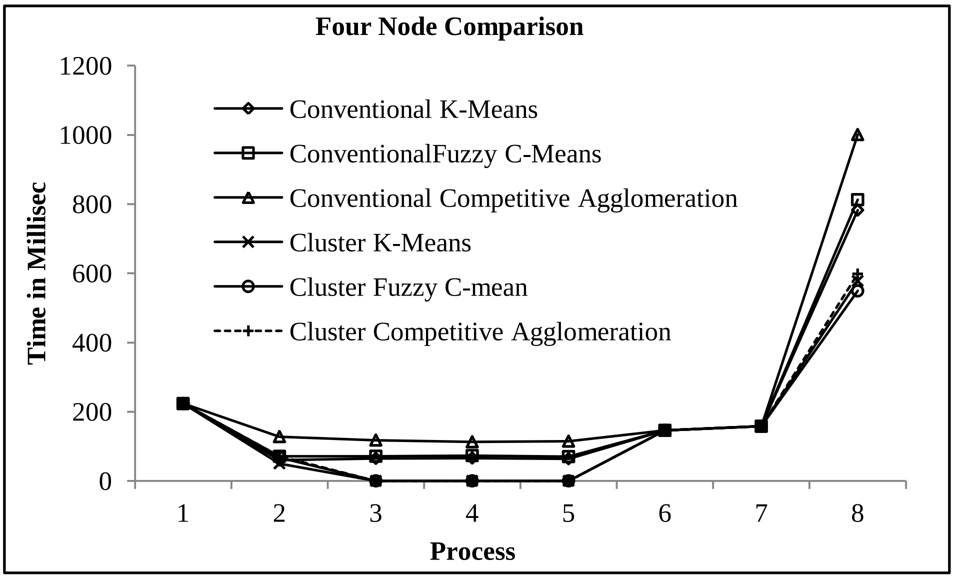


Fig.10. Four Nodes - Conventional Vs Cluster Methods

Table.2 Four Nodes - Conventional Vs Cluster Method and Fig.10 describes the Four Nodes - Conventional Vs Cluster Methods for faster and secure processing.

Table.3. Sixteen Nodes - Conventional Vs Cluster Methods

Sl. No.	Process (Time taken)	Conventional Methods (ms)			Cluster Methods (ms)		
		K-Means	Fuzzy C-Means	Competitive Agglomeration	K-Means	Fuzzy C-Means	Competitive Agglomeration
1	Split Operation	223.46	223.46	223.46	223.46	223.46	223.46
2	Segmentation(Block-AI) Operation	40.51	42.56	48.86	35.67	40.90	41.23
3	Segmentation(Block-AII) Operation	35.46	43.05	47.86	-	-	-
4	Segmentation(Block-AIII) Operation	32.45	41.09	42.96	-	-	-
5	Segmentation(Block-AIV) Operation	31.87	47.08	44.81	-	-	-
6	Segmentation(Block-BI) Operation	40.09	44.98	46.86	-	-	-
7	Segmentation(Block-BII) Operation	38.76	42.21	47.86	-	-	-
8	Segmentation(Block-BIII) Operation	37.90	45.98	42.96	-	-	-
9	Segmentation(Block-BIV) Operation	35.78	47.67	41.81	-	-	-
10	Segmentation(Block-CI) Operation	34.90	40.98	47.86	-	-	-
11	Segmentation(Block-CII) Operation	34.05	41.23	45.86	-	-	-

12	Segmentation(Block-CIII) Operation	39.90	40.45	42.96	-	-	-
13	Segmentation(Block-CIV) Operation	38.76	42.90	44.81	-	-	-
14	Segmentation(Block-DI) Operation	35.67	41.23	47.86	-	-	-
15	Segmentation(Block-DII) Operation	34.56	43.23	47.86	-	-	-
16	Segmentation(Block-DIII) Operation	32.90	45.67	42.96	-	-	-
17	Segmentation(Block-DIV) Operation	38.76	41.23	44.81	-	-	-
18	Merge Operation (Seconds)	147.96	143.96	147.96	143.96	147.96	143.96
19	Show Operation (Seconds)	153.95	153.95	153.95	153.95	153.95	153.95
	Total Time	1107.69	1212.91	1254.33	557.04	566.27	562.6

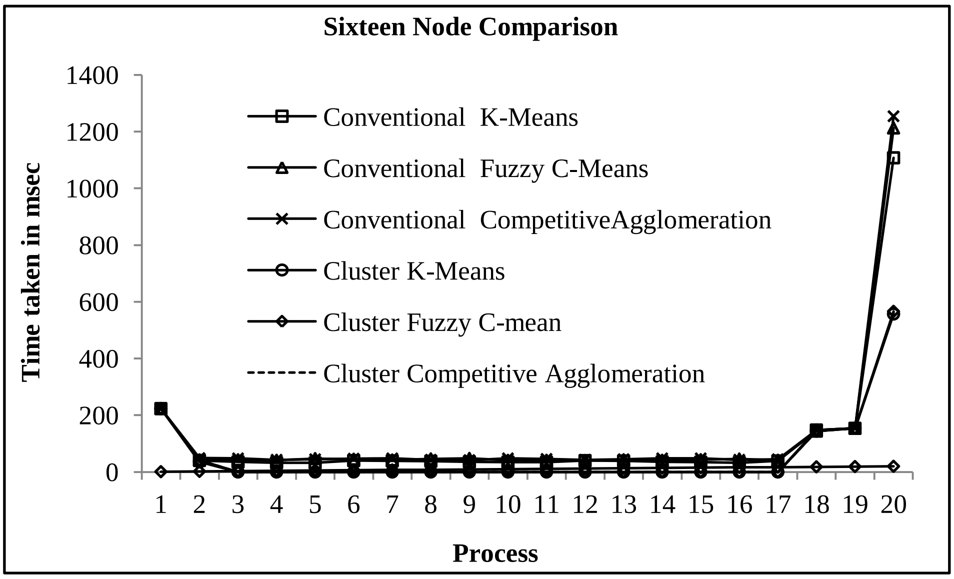


Fig.11. Sixteen Nodes - Conventional Vs Cluster Method

Table.3. Sixteen Nodes - Conventional Vs Cluster Method and Fig.11describes the Sixteen Node - Conventional Vs Cluster Methods for faster and secure processing.

Table.4. Conventional Vs Cluster Method

Sl. No.	Process (Time Taken)	Conventional Methods (ms)	Cluster Methods (ms)
1	Single Node	1017.86	652.23
2	Four Nodes	984.82	639.2
3	Sixteen Nodes	1254.33	566.23

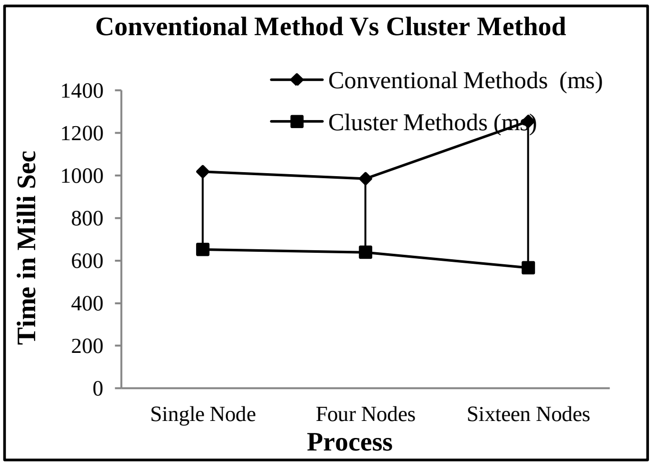


Fig.12. Conventional Method Vs Cluster Method

Table.4 Conventional Vs Cluster Method and Fig.12 describes the Conventional Vs Cluster Method for faster and secure processing.

The performances of the clustering techniques applied on the CT scan images of the brain should be evaluated based on the parameters such as number of clusters selected and the time complexity measured for each algorithm. Hence, the performance of the clustering techniques is analyzed depending on the parameters.

9. APPLICATIONS

The clustering techniques are also used to locate the tumors of the brain which is one of the medical imaging applications.Our proposed method can be applied for Realtime Medical Imaging for brain tumor detection in a faster and to produce effective result.

10. CONCLUSION

This clustering environment was tested against standard environment in order to rate it. From the analysis result it has been found that clustering environment stands unique in providing secure and faster service to the user compared to the other methods. A comparative analysis is made after applying the clustering techniques on both CT scan brain images and the tumored brain images. The algorithms are analyzed based on the parameters such as time complexity, number of clusters and the performance of the algorithm which would bring the better results. It is observed that as the number of clusters increases then the time taken to execute the algorithms would also be increased and sometimes decreased for few number of clusters when applying the K-Means Clustering and Fuzzy C-Means Clustering techniques. Since both algorithm suffers from the same problem as they depends on the initial selection of cluster centers.

The competitive agglomeration clustering takes more time while comparing with other clustering algorithms but with effective results.

In our Proposed method is implemented using Matlab[22] and Java[21] based Cluster Environment. Several set of Images are tested based on this approach and its speed is measured. This method gives higher efficiency rate than other schemes. The Security Level is higher because the operations are done inside a java cluster Nodes and Master Node. Our Project is efficient to a mark of 98.43% comparing others.

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