International Journal of Contemporary Research in Computer Science and Technology (IJCRCST) e-ISSN: 2395-5325
Volume 5, Issue 3 (September '2019)

ANALYSIS OF CLUSTERING METHODS IN IMAGE SEGMENTATION

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Abstract: In computer vision, image segmentation is the process of partitioning a digital image into multiple segments according to sets of pixels. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. The main task of exploratory data mining, and a common technique for statistical data analysis, used in many fields, including machine learning, pattern recognition, image recognition, image analysis, information retrieval, bioinformatics, data compression and computer graphics. Many clustering algorithms are used for analyzing an image. In this paper we have used two algorithms k-means clustering and Adaptive k-means clustering. K-means clustering algorithm belongs to Partitional clustering. It is widely used in image processing specially in image segmentation. K-means clustering segments the images but not gives satisfactory results of desire objects. To overcome the problems we used Adaptive k-means clustering algorithm. Both the algorithms implemented on images of different resolutions and compared the performance of the segmented images. The performances are compared based on some parameters. The parameters are PSNR, RMSE, SSIM, Elapsed time period. From each and every comparison we have concluded that the Adaptive k-means clustering gives better result as compared to k-means clustering. By using these techniques we can isolate any target object from medical images specially detection of cancerous data. Both the algorithms also implemented in other fields like telecommunication, scientific especially high resolution images.

Keywords: - Image segmentation, k-means clustering, Adaptive k-means clustering, MRI images, and image resolution, PSNR, RMSE, and SSIM etc.

I. INTRODUCTION

Now-a-days the medical industry, astronomy, physics, chemistry, forensics, remote sensing, manufacturing, and defense are just some of the many fields that rely upon images to store, display and provide information about the world around us. The challenge to scientists, engineers and business people is to quickly extract valuable information from raw image data. This is the primary purpose of image processing – converting images to information. Digital image processing is the use of computer algorithms to perform image processing on digital images. A digital image is an array of real numbers represented by a finite number of bits. The basic advantage of Digital Image Processing methods is its versatility, repeatability and the preservation of original data precision. The various Image Processing techniques are: Image Enhancement, Image Restoration, Image Compression, Image segmentation, Image classification, Feature Extraction, Representation etc. In image processing, some techniques are used to detect the tumour cell among which image segmentation takes a major role in analyzing the image. Selkar and Prof. Thakare (2014) [1] and Gonzalez and Woods (2004) [2] Image segmentation is a process that subdivides an image into its constituent parts or objects. The level to which this section is carried out depends on the problem being solved, i.e., the segmentation should stop when the objects of interest in an application is isolated by using different techniques. In the same process the tumour cell can be detected and extracted for analyses from an Image. Out of different techniques of segmentation clustering is the most efficient one. There are different types of clustering namely k-means clustering, Fuzzy C means clustering, hierarchal clustering and Adaptive k-means clustering. In recent days, cancer is the most common disease by which whole world is suffering. It is also one of the most burning topics that are under discussion among various researchers and it is the demand of time to improve the survival rate of the cancer patients by early detection. Multiplication of a set of cells in a particular area of our body and the growth of the cells are uncontrollable, this is one type of structural distortion of cells that are mentioned as tumour. It is very important to know the perfect spreading area of tumour cell to cure the diseases (Chitade, A.Z.) [3]. by using the segmentation techniques in MRI (Magnetic Resonance Image) the tumour cells are very easily detected with its accurate spreading area. There is no particular region in our body where we can say that the cancer cell will develop. Cancer cells developed in the brain are mostly focused, because of the fact that it is based on Neurodegenerative disorders, which may lead to memory loss, hearing loss, dizziness etc. Brain tumour is one of the major causes for the increase in mortality rate among the children and adults. A tumour is a mass of tissue that grows-out of control from the normal forces which regulates growth. Therefore, identification of these diseases helps in the recovery of patients by suggestive and corrective treatments. Clustering belongs to an unsupervised image classification, where one can point out a finite set of categories termed as clusters to describe the data. Unlike classification that analysis class-labeled instance, clustering has no initial stage, and is usually used when the classes don't know in advance. A similar metric is outlined between things of information, and so similar things are classified along to make clusters. Often, the attributes providing the most effective clustering should be likewise known. The grouping of information into clusters is based on the principle of maximizing the intra class similarity and minimizing the interclass similarity. Properties about the clusters are analyzed to work out cluster profiles that distinguish one cluster from another. A decent clustering technique can turn out high quality clusters with high intra-class similarity - similar to each {other} at intervals a similar cluster low inter-class similarity - Dissimilar to the objects in other clusters the standard of a clustering result depends on both the similarity measure used by the strategy and its implementation. The standard of a clustering technique is additionally measured by its ability to find some or all of the hidden patterns. (Gopi, E. S.) [4] The clustering based techniques are the techniques, which segment the image into clusters having pixels with similar features. Data clustering is the method that divides the data elements into clusters such that elements in same cluster are more similar to each other than others. Among all the clustering techniques k-means clustering is widely used because of its simplicity. In other words k-means is an algorithm to classify or grouping objects based on attributes/features into k number of groups where k is positive integer number. The combination is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. Thus, the purpose of k-mean clustering is to classify the data. The number of k is a user defined number. The value of k is selected in different ways. (Pham. D T, et al.) [5]

- When k-means clustering is used as a pre-processing tool, the number of clusters is determined by the specific requirements of the main processing algorithm.
- Values of k calculated to the number of generators- the clustering performance is judged on the basis of the difference between objects covered by a cluster and that are created by the corresponding generator.
- There are several statistical measures available for selecting k. These measures are often applied in combination with probabilistic clustering approaches.
- Values of k equated to the number of classes in the data set.
- Values of k determined through visualization, it is applied widely because of its simplicity and explanation possibilities.
- Values of k determined using a neighborhood measure- A neighborhood measure could be added to the cost function of the k-means algorithm to determine k.

Another algorithm, which is considered here, is Adaptive k-means clustering. Both k-means and Adaptive k-means clustering method are widely used in image segmentation. These algorithms are simple and faster than other clustering. Both are used for work in a large number of variables. In case of k-means, initialization of the value of k takes an important task where as in Adaptive k-means it is not required to initialize the value of k, based upon some features and characteristics the image will automatically finalize the value of k. (Bhatia, S.K.) [6] Image segmentation takes an important role to analyze the extracted region in medical images or MRI in medical area. So, medical images are segmented for further analysis by using different techniques of image segmentation. For analyzing the medical images, one of the fundamental problems is to identify the boundaries of an object such as organs, abnormal regions in images. From the result of segmentation it is possible for shape analysis, detecting volume change and making accurate radiation therapy treatment plan. By using both the algorithms, we extracted the desired area of tumour spreading in brain MR gray and color images, whereas in the high-resolution images, one can easily isolate the cover area of any object. From the segmented images, we have compared some parameters based on various test metrics like PSNR, RMSE, Elapsed Time Period and Quality of an image (Dhanachandra, N.) [7].

II. REVIEW OF LITERATURE

2018, **C. Latha, *et al.* [8]** in this research, the Fitness function in GA (Genetic Algorithm) based FCM (Fuzzy C-Means) clump and Morphological operation is used to extract tumor from MRI. The new FCMFF in GA is applied on few images additionally to experiment results of recital are compared along by means of analysis of the ground truth image. In this work a comparative study of a variety of performance metrics are made. This research evaluates the performance of Fuzzy c-means, Threshold-based Fuzzy C-Means segmentation, Probability-based Fuzzy C-Means and FCMFF in GA The accuracy, MAE ,Dice overlap, JI,JD,MSE,RMSE,PSNR,BDE of various segmentation techniques are reported. The FCMFF in GA segmentation gives a better result on considering the whole performance.

2018, N.Harini, *et al.* [9] the main aim of this research is to reduce noise effects in the process of image segmentation where FCM plays major role in de-noising and maintaining detail information. In this research, Haar Wavelet Transform (HWT) is used in many methods of discrete image transforms and processing. In addition, at the output side Support Vector Machine (SVM) algorithm is used, this classifies the image by comparing the features of given image with that of the trained image. The proposed system uses a parameter which tradeoffs the noise sensitivity and preserving the information of the image in an effective manner. The use of fuzzy color creditability approach to color image filtering. However, in this research, to obtain an exact limit of the regions, every empirical dispersion of the image is computed by Fuzzy C-Means Clustering (FCM) segmentation. A classification process based on the Support Vector Machine (SVM) classifier is accomplished to distinguish the normal tissue and the abnormal tissue.

2017, Dongling Liu, *et al.* [10] the proposed algorithm (improved fuzzy c-means) is used in brain MR image segmentation. The results showed the proposed algorithm has better edge characteristic. In order to test the performance of proposed scheme, brain MR image of 128 X 128 pixels are used in the experiment. The grayscale is between 0 to 255. FCM and improved FCM algorithm take gray level as characteristic. The fuzzy c-means and enhanced fuzzy c-means algorithms are compared in this research. It can be seen that the proposed algorithm can ensure the continuity of the image edge compared with FCM algorithm.

2017, J. Kowski Rajan, *et al.* [11] in this research, a color image segmentation using support vector machine (SVM) pixel classification is proposed. Firstly, the pixel level color and texture features of the image are extracted and they are used as input to the SVM classifier. These features are extracted using the homogeneity model and Gabor Filter. With the extracted pixel level features, the SVM Classifier is trained by using FCM (Fuzzy C-Means).The image segmentation takes the advantage of both the pixel level information of the image and also the ability of the SVM Classifier. Finally, the color image is segmented with the trained SVM model. Results obtained on the Berkeley segmentation database indicate that the proposed algorithm achieves better quantitative results than the segmentation methods recently proposed in the literature. Drawbacks of the proposed image segmentation are that it lacks enough robustness to noise.

2017, G.Ravindran, *et al*. [12] In this research analyze and compare the gray level texture feature techniques, number of clusters, Fuzzy C means, and to find which algorithmic approach provides better results in image segmentation. The proposed image clustering technique is verified in MATLAB software and compared the features with conventional clustering techniques. First step to convert the grey after that find the cluster based on number of cluster and analyze the mean cluster value. The number of cluster involved in this research is 2. The k-means algorithm in this research a number of cluster used 3. The five parameters such as Contrast, Correlation, Energy, Homogeneity and Entropy are found by using GCLM technique. By using K mean, Fuzzy C means calculate the cluster mean from the each cluster. Similarly, modify the number of clusters to find the cluster mean from each cluster. Comparison between the segmentation techniques such as k means and the GLCM, K means provide the best details of texture feature. Similarly, comparison between the K means and C Means clustering algorithm, FCM provides the accuracy values.

2016, Min Li, *et al*. [13] proposed an improved algorithm based on FCM clustering for segmentation of brain MRI data. The MRI data used in this study was provided by the Third Military Medical University and the image matrix was 512 pixels x 512 pixels. In order to evaluate the performance of the proposed improved FCM method, our segmentation results are compared with those produced using the EM method and the conventional FCM algorithms. In this research showed the comparison of segmented WM, GM and CSF produced by different methods for representative slice images. The images in the first column showed the original brain MRI images. Images in the second column are the results produced by EM algorithm. Images in the third and fourth columns are the results produced by the conventional and improved FCM methods respectively. Results indicate that the improved FCM method produces more accurate and reasonable segmentation of WM, GM and CSF from MRI data.

2016, Hind Rustum Mohammed, *et al.* [14] This research produced an improved fuzzy c-mean algorithm that takes less time in finding cluster and used in image segmentation. Tested Improved fuzzy c-mean by implemented by using MATLAB and compared it with implementation of fuzzy c-mean algorithm that used by MATLAB by calling command fcm, in this research try algorithm in database of images contains 100 images, in the following the research provide a sample from tested images, in this testing sample the cluster is used C=3:. From above results in accuracy and speed of proposed fuzzy c-mean algorithm compared with the traditional fuzzy c-mean algorithm, the proposed algorithm is a great enhancement in implementation and performance of traditional fuzzy c-mean.

2016, Shiling Sun, *et al.* [15] this research mainly studied the image segmentation based on the traditional FCM algorithm, and proposed a fast fuzzy clustering algorithm. The experimental results showed that the proposed algorithm has some advantages. This research adopts brain MRI images of the Montreal neurological institute for simulation. Traditional clustering image segmentation result, traditional FCM image segmentation result and image segmentation result of proposed algorithm is compared in this research. The proposed fast image segmentation is superior to the traditional algorithm, the edge details is clear, this algorithm can ensure clustering optimization performance unchanged, reduce the cost of operation, and obviously improves the segmentation efficiency.

III. K-MEANS ALGORITHM

K-means algorithm is used for initialization of parameters since it is simple and works well for large data sets when compared with hierarchical clustering. (Dhanachandra, N.) [7] and (Kardi, T.) [16]. According to some similarity measure (e.g. Euclidean) the data are divides into a specific number of groups that group number is noted as 'k' variable where k=1, 2, 3…………n. it is a user defined number. The group of same data is called as clustering and the method is called as k-means clustering. This algorithm is consisting of two separate phases. At first it calculates the k centroid and secondly it takes each point to the cluster which has nearest centroid from the adjacent data point. To find out the distance of nearest centroid it will used the Euclidean distance method. After the grouping of the data it finds out centroid of each cluster.

The Euclidean distance is calculated among each center and each data point assigns in the cluster which have minimum Euclidean distance, after reassigning the points each time the centroid of the clusters are recalculated. This process is continued till the end of the rest points then finally it calculated the final centroid or mean of the clusters. So k-means is an iterative algorithm in which it means the sum of distance from each object to its cluster centroid, over all clusters. (Dhanachandra, N.) [7] Let us consider an image $m \times n$ and the image has to be cluster into k number of cluster. Suppose a point f(x, y) which is an input pixels to be cluster and C_K be the cluster center. The algorithm of k-means clustering is shown as follows:

- First, initialize the number of cluster K and calculate their center CK by using the formula
$$C_K = \frac{\text{Number of cluster K} * \text{no.of pixels}}{K+1}$$
- Calculate the Euclidean distance Ed between the center and each pixel of an image using the relation given below.
$$E_d = \|f(x,y) - C_K\|$$
- Based upon the Euclidean distance Ed assigns the rest pixels to the nearest cluster.
- After assigning all the pixels in the appropriate cluster the value of the cluster center should be changed and it is calculated by using the relation given below:
$$X_K = \frac{1}{K}\sum_{y \in Ck}\sum_{x \in Ck} f(x,y)$$
- Reiterate the process till it satisfies the tolerance or error value.
- Update the cluster mean i.e. calculate the mean of the object for each cluster.

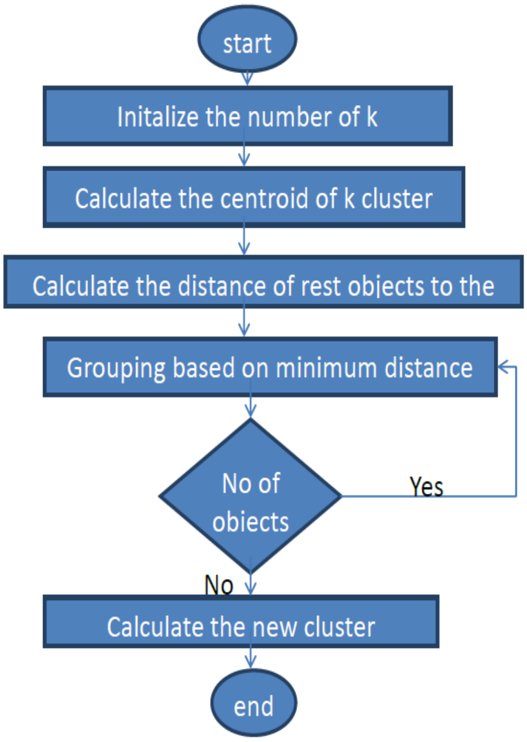

Figure 1: Flow chart of k-means clustering

Data base colour image segmentation implementing k-means clustering

- Read the data base colour image one by one.
- For colour separation of an image apply the Decor relation stretching.
- Now, convert one by one data base colour image from RGB colour to L*a*b colour.
Here, The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where colour falls along the red-green axis, and chromaticity-layer 'b*' indicating where the colour falls along the blue-yellow axis. All of the colour information is in the 'a*' and 'b*' layers. We can measure the difference between two colours using the Euclidean distance metric. Convert the image to L*a*b* colour space. (Chitade, A.Z.)[3]
- Applying the k-means clustering, based upon the Euclidean distance classify the colours of each image in 'a*b*'.
- Using k-means result labels every pixel in the image.
- We will get three clusters of Black, White and gray segmented image at the output, which one create segmented data base image by colour.

IV.ADAPTIVE K-MEANS CLUSTERING

In Adaptive k-means clustering algorithm the number of k is selected from data set and it is randomly selected based upon some characteristics and features. The properties of each element also form the properties of the cluster that is consisting by the element. (Bhatia, S.K.) [6] and Shinde and Tidke (2013) [46] Like k-means clustering this algorithm is also compute the distance between a given element and a cluster. So the function of the algorithm is based upon to compute the distance between two elements. This function has an important consideration i.e. it should be able to count for the distance based on properties that have been normalized so that distance is not dominated by one property or some of the property is not ignored in the computation of distance. It uses Euclidean distance formula for compute the distance. For example: when spectral data specified by n-dimensions, the distance between two data elements. $D_1=\{D_{11},D_{12},\ldots\ldots D_{1n}\}$and $D_2=\{D_{21},D_{22},\ldots\ldots D_{2n}\}$ The Euclidean distance is given by

$$E.D = \sqrt{(D11 - D21)^2 + (D12 - D22)^2 + \ldots + (D1n - D2n)^2}$$

Based upon the distance the adaptive k-means clustering algorithm is as follows:

At first find out the distance of each cluster from every other cluster and it is stored in a 2D array as a triangular matrix. The minimum distance Dmin between any two clusters C1 and C2 was noted. Compute the E.D distance from each cluster to each un clustered element. In this case there are three possibilities for assignment of the rest element to the suitable cluster that are like below four forms.

1. When the distance is zero from an element to a cluster then that element is assigned in that cluster, and then proceeds for next element.
2. The next element is allocated to its closest cluster if the distance of an element from a cluster is less than Dmin. After reassigned the element in the cluster the centroid of the cluster is changed. So according to the properties of the elements the centroid is recomputed. As well as we recomputed the distance of the affected cluster from every other cluster, also the minimum distance between any

two clusters and the two clusters they are closest to each other.

3. Finally, it is computed when the distance Dmin is less than the distance of the element from the nearest cluster.
4. We take two closest clusters C1 and C2, and then merge C2 into C1. Now we get only one cluster C1 and we destroy the elements as well as the representation of C2, so C2 called as empty cluster. We get a new cluster successfully. Again the distances between all clusters are recomputed and two closest clusters recognized again.
5. Till all the elements has been clustered the above three steps are to be repeated. By this way we should cluster the elements without defining the number of k in adaptive k-means clustering.

V.EXPERIMENTAL RESULT

The analysis the results of the both algorithms we used some parameters. By comparing those parameters we can prove that which is a good algorithm for clustering and data detection. So for comparing the results of the algorithm the following parameters are used.

5.1 RMSE (root mean square error)
5.2 PSNR (peak signal to noise ratio)
5.3 Elapsed time period
5.4 Image Quality

5.1 RMSE (Root mean square error)

The Root Mean Square Error (**RMSE**) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modeled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. (Dhanachandra, N.) [7] It has been used for the standard performance measurement of the output image. It gives how much output image is deviated from the input image. The equation of

$$\text{RMSE}=\sqrt{\frac{1}{n_x n_y}\,\frac{\sum_0^{n_x-1}\sum_0^{n_y-1}[(r(x,y))]^2}{\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)-t(x,y)]^2}}$$

5.2 PSNR (Peak signal to noise ratio)

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of reconstruction of lousy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content. The peak signal to noise ratio is the proportion between maximum attainable powers and the corrupting noise that effect likeness of image. It is used to measure the quality of the output image. (Dhanachandra, N.) [7].

$$\text{PSNR}=10.\log_1 0\left[\frac{max(r(x,y))^2}{\sqrt{\frac{1}{n_x n_y}\,\frac{\sum_0^{n_x-1}\sum_0^{n_y-1}[(r(x,y))]^2}{\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)-t(x,y)]^2}}}\right]$$

5.3 Elapsed time periods

The time has taken in MATLAB Gonzalez and Woods (2004) [17] during running of both the algorithm. By using a MATLAB command Tic….Toc we calculate the running time of both the algorithms. After the time period noted by comparing we have compared which takes less time for running of program. After calculation comparing of ruining time we concluded which Program is best for clustering and data detection.

5.4 Image quality

Image quality is a characteristic of an image that measures the perceived image degradation (typically compared with an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem. For measuring the image quality in MATLAB we used a function called Structural Similarity Index (SSIM). Image quality is a characteristic of an image that measures the perceived image degradation (typically compared with an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem. For measuring the image quality in MATLAB we used a function called Structural Similarity Index (SSIM).

Comparison analysis of the Parameters result

For comparison of parameters we took the clustered image with the original image and calculated the RMSE, PSNR, SSIM values & finally the time taken during the running of the program was noted as elapsed time period. We had compared the clustered image parameters results of both the algorithms to find out which algorithm is the best. (Bhalodiya, K.)[18]. The comparison of parameters & the analysis of their results are shown in Table 1.

Image	RMSE			PSNR			Elapsed time			Quality of image		
	k-means	Adaptive k-means	Analysis	k-means	Adaptive k-means	Analysis	k-means	Adaptive k-means	Analysis	k-means	Adaptive k-means	Analysis
Gray colour Brain (MRI)	16.957	13.823	The root mean square value as per the name indicates the lesser value indicates better process	8.408	10.341	The Peak signal to noise ratio as the name suggests the higher value indicates better process.	0.458	0.397	Elapsed time as the name indicates the process in shorter time span is the better process	0.255	0.228	This SSIM value in case Gray Scale image is better in k- means But it shows better value with colour image in Adaptive k-means. This variation is due to the pixel depth in case of colour images.
Gray colour Knee cancer(MRI)	21.520	21.045		4.701	4.773		1.756	0.588		0.015	0.023	
colour Brain(MRI)	22.730	20.034		8.261	12.483		0.173	0.159		0.186	0.372	
High resolution (1278×798)	25.064	24.142		8.573	8.702		0.135	0.073		0.177	0.213	
Resolution-1 (600 ×439)	22.817	21.767		9.656	9.730		0.232	0.103		0.297	0.337	
Resolution-2 (470 ×467)	18.570	18.347		9.303	9.331		0.125	0.092		0.435	0.447	

Table 1: Parameters comparison & their Analysis

For the comparison at first we took the gray colour MRI image. In case of k-means clustering the clustered 3 image choose as segmented image. Whereas in case of Adaptive k-means clustering the clustered 2 image choose as segmented image.

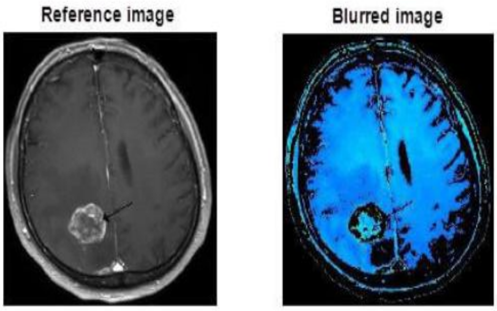

Figure 2:(a) Original image (b) Cluster3 image

Figure 3: SSIM image & the results of k-means clustering

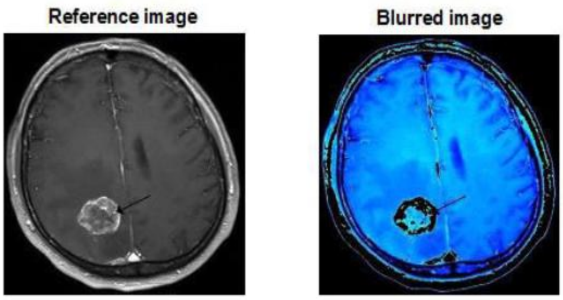

Figure 4: (a) Original image (b) Cluster2 image

Figure 5: SSIM image & the results of Adaptive k-means clustering

From the parametric comparison table 5.1 we found that the RMSE value of k-means is 16.957 and Adaptive k-means is 13.823. According to the definition if the RMSE value is more, then the error is more. Here, k-means clustering algorithms RMSE value was more as compared to Adaptive k-means clustering algorithm. So we have concluded here that the Adaptive k-means is better as compared to kmeans. In case of PSNR, the values of k-means and Adaptive k-means were 8.408 & 10.341. As the name suggests the higher value indicates better process. Here, the Adaptive k-means clustering algorithm value was more as compared to k-means clustering algorithm. So, Adaptive k-means clustering is better than k-means clustering. When we calculated the Elapsed time periods of both algorithms, Adaptive k-means clustering took 0.397 sec and k-means took 0.458sec. So from the time period result we had concluded that Adaptive k-means takes less time as compared to k-means. From the figure 2(c) & 2(c) we find out the structural similarity index map value is 0.255 in k-means algorithm and 0.228 in Adaptive k-means clustering algorithm. Here we have found the SSIM value was more in k-means clustering algorithm but less in Adaptive. So we have concluded the in gray colour image the SSIM value is higher in k-means. Similarly, we had taken a gray colour knee cancer MRI image. Here we find the cancer portion of the knee. For the comparison, at first we applied the k-means clustering in the image. Here we took k=4, the clustered image_3 was used as a segmented image result. Also in case of Adaptive k-means clustering we had taken clustered image_2 as segmented image. Both clustered image results were compared with the original image for calculating the RMSE, PSNR, SSIM value & finally noted the time period. The cluster images and the SSIM image of both algorithms were as follows.

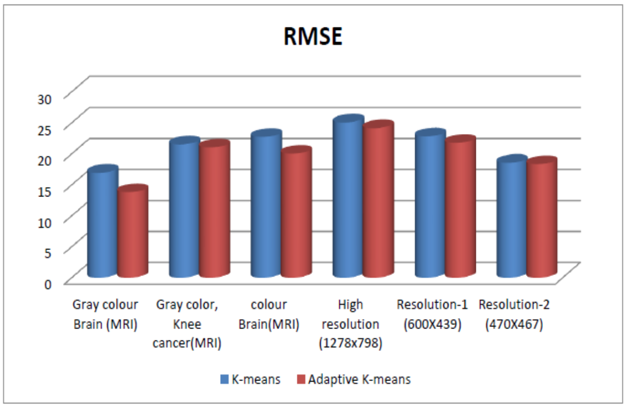

Figure 6: Graphical representation of RMSE

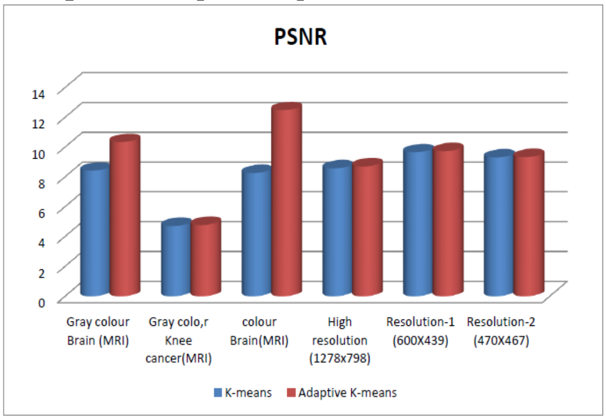

Figure 7: Graphical representation of PSNR

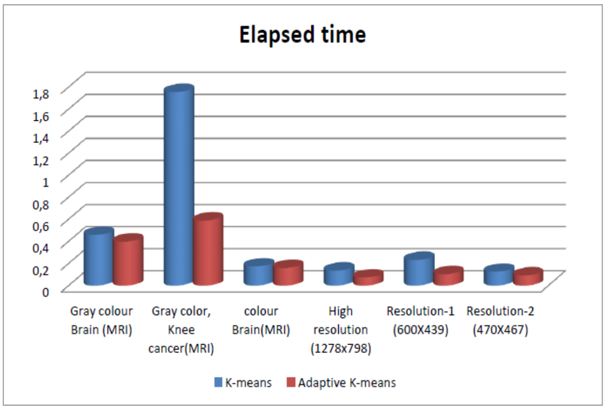

Figure 8: Graphical representation of Elapsed time periods

Figure 9: Graphical representation of Quality of an image

In figure 6, the graph represents RMSE in k-means as compared to Adaptive k-means algorithm. It defines that the Adaptive k-means clustering image is less deviated as compared to kmeans clustering image. (Bhalodiya, K.)[49] Where as in PSNR, which defines the noise in an image is less in Adaptive k-means as compared to k-means clustering algorithm as shown in the Figure 7 graph. In case of time period, Adaptive kmeans takes very less time as compared to k-means that can be defined from the figure 7. (Bhalodiya, K.)[18]. The Adaptive k-means clustering took less time as compared to k-means clustering it is shown in figure 8. When we compare the quality of an image by SSIM value in case of gray colour image it is less in Adaptive k-means clustering and more in k-means clustering. Whereas in colour image and high resolution colour images the SSIM value is high in Adaptive k-means clustering and less in k-means clustering. From this result we prove that the isolation of any object in colour image is clearly visualize and separated perfectly by using Adaptive k-means clustering, this result shows in figure 9.

VI.CONCLUSION

The analysis are based on the values of the parameters like PSNR, RMSE, Elapsed time period & quality of image (SSIM) both the segmented images parametric results are compared. From the results we found Adaptive k-means clustering result was better than k-means clustering. But only the SSIM value was found more in k-means clustering algorithm of gray colour image. The results of SSIM values on other images were clearly discussed in other resolution images. Then we have taken a knee cancer image for detection of cancerous data. Here also Adaptive was better as compared to k-means clustering algorithm. Then we have taken a colour brain MRI image. Here also we have applied both algorithms in that image. From the segmented images we had chosen the clustered image from both algorithms. The result of the colour brain MRI clustered images were compared and found out that, Adaptive was better as compared to k-means clustering algorithm.

VII. REFERENCES

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