

# Performance Analysis for Quality Measures using K means Clustering and EM Models in Segmentation of Medical Images

R. HariKumar, B. Vinoth kumar , G. Karthick

**Abstract**— *The main objective of this paper is to compare the performance of quality measures towards the segmentation of medical images using K-means clustering and EM models. Three types of medical images such as MRI, X-rays and Ultrasonic images are studied. The K-means clustering shows that the non intactness of the clusters. As cluster size increases the edges are brittle and compactness of the clusters get altered. Hence expectation maximization models are utilized to segment the images for better edge perseverance and compactness of clusters at larger size. The quality measures like PSNR, average difference, structural content, image fidelity and normalize coefficients are calculated for both methods. The EM models shows one dB increase in PSNR values than the K-means clustering. At less number of clusters AD value of EM models mitigates the compactness of the cluster centers.*

**Index Terms**— *Segmentation, K-means clustering, EM models, Quality measures*

## I. INTRODUCTION

Segmentation is a fundamental process in digital image processing which has found extensive applications in areas such as medical image processing, compression, diagnosis arthritis from joint image [1] [2], automatic text hand writing analysis [3], and remote sensing. Numerous algorithms using different approaches have been proposed for image segmentation. These approaches include local edge detection [4], deformable curves [5], morphological region-based approaches [6] [7], global optimization approaches on energy functions and stochastic model- based methods [8][9]. Some intensity-based methods such as thresholding and histogram-based finite mixture models are easy to be formulated and fast. However they often fail to segment objects with low contrast or noisy images with varying background. It is noted that these methods don't use the spatial morphological images information [10]. On the other hand, some other methods such as morphological segmentation, region growing and deformable curves, mainly focus on spatial information such as local structures or

regions. Unfortunately, the majority of these techniques are not suitable for satellite image segmentation [11].

In this context, it is important to develop unsupervised segmentation methods capable of analyzing and classifying these images. Indeed, recently, there has been considerable interest in stochastic model-based image segmentation techniques. In such techniques, an image is separated into a set of disjoint regions with each region associated with one of finite numbers of classes that are characterized by distinct parameters. In fact, it exist two different statistic image segmentation approaches, the supervised approach, and the unsupervised approach. In supervised approach, it is usually assumed that training data are available for the image classes; therefore, the parameters can be estimated from the training data before segmentation. But, this is rather unrealistic in many practical situations. For unsupervised techniques, the objective is to estimate the parameters and segment the image simultaneously [15]. Most of the proposed solutions to the unsupervised segmentation problem can be classified into two broad categories; one is a two-step procedure, estimating the parameters for each class and then using a relaxation scheme to do segmentation [16]. The other is an iterative procedure, which starts with initial parameters and alternatively segments the image based on current parameters and estimates parameters based on current segmentation as if it were correct. In the first category, clustering algorithms are usually adopted to estimate the classes parameters. In the second category, parameters are estimated in each iteration using the current segmentation as if it were correct and the estimated parameters are used in the next segmentation as if they were true parameters. Although these techniques have demonstrated substantial success for satellite image, they have some limitations. Indeed, most of the statistical image segmentation techniques need a manual initial input such as the classes number. Meanwhile, these methods are often sensitive to these initial conditions. Moreover, all these methods cannot segment correctly the entire image, if the initialization step is not optimal. In this paper an optimal initialization methods based on K-means approach's, for a better unsupervised medical image segmentation is studied. A two step EM model is utilized for segmentation of medical images. The quality measures are calculated for both the methods and their efficacy are reported.

**Manuscript received November 2, 2011.**

**Dr.R.Harikumar**, Professor, ECE Department, Bannari amman Institute of Technology, Sathyamangalam, India 9942932239 (e-mail: harikumarrajaguru@gmail.com).

**B. Vinoth kumar**, Assistant Professor (Senior Grade), EEE Department, Bannari amman Institute of Technology, Sathyamangalam, India 9952475500 (e-mail: bojanvinoth@gmail.com)

**G. Karthick**, PG Scholar, ECE Bannari Amman Institute of Technology, Sathyamangalam, India 9344558697 (e-mail: karthick.sgs@gmail.com)

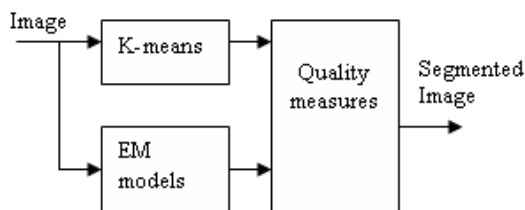
## II. GENERAL CLUSTERING ALGORITHM

During last decades, growing attention has been put on data clustering as robust technique in data analysis. Clustering or data grouping describes important technique of unsupervised classification that arranges pattern data (most often vectors in multidimensional space) in the clusters (or groups). Patterns or vectors in the same cluster are similar according to predefined criteria, in contrast to distinct patterns from different clusters [12, 13].

Possible areas of application of clustering algorithms include data mining, statistical data analysis, compression, vector quantization and pattern recognition [12, 13]. Image analysis is the area where grouping data into meaningful regions (image segmentation) presents the first step into more detailed routines and procedures in computer vision and image understanding.

Clustering problem understood as grouping input data by means of minimizing certain criteria presents NP-hard combinatorial optimization task.

Fig. 1. Enumerates the block diagram of cluster based segmentation of medical images using K-means clustering and EM models. The motto of this research is to segment the images and measure their quality parameters of the above methods. The quality measures are obtained for the center based K-means clustering and EM models. Comparison of both the methods are analyzed.



**Figure 1. Block Diagram for Cluster Based Segmentation of Medical Images**

“Center- based clustering” refers to the family of algorithms that use a number of centers to represent and group input data. General iterative model for partition center-based clustering algorithms has the following form [14, 15 and 16]:

1. Data initialization by assigning some values to the cluster centers.
2. For each data point  $x_i$ , calculate its membership valued  $m(c_j | x_i)$  to all clusters  $c_j$  and its weight  $w(x_i)$ .
3. For each cluster center  $c_j$ , recalculate its location taking into account all points  $x_i$  assigned to this cluster according to the membership and weight values:

$$C_j = \frac{\sum_{i=1}^n m(c_j | x_i) w(x_i) x_i}{\sum_{i=1}^n m(c_j | x_i) w(x_i)} \quad (1)$$

4. Repeat steps 2 and 3 until some termination criteria are met.

Data clustering presents unsupervised process that finally requires some sort of quality evaluation of generated clusters. This requirement can be satisfied by using cluster validity indices,[17,18]. 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.

## III. K - MEANS CLUSTERING

K-means clustering algorithm proposed by Mac Queen in 1967 belongs to partitioning methods, which is widely used because of its simpleness and fast convergence. The primary process can be expressed as follows [19, 20].

1. Initialize K cluster centers chosen randomly.
2. Assign each  $x_i$  to its nearest cluster center  $c_k$  by Euclidean

$$\text{Distance (d). } KM(X, C) = \sum_{i=1}^n \min_{j \in \{1, \dots, k\}} \|x_i - c_j\|^2 \quad (2)$$

$$d(p, q) = d(q, p) = \sqrt{\sum_{i=1}^n (q_i - p_i)^2} \quad (3)$$

3. Update each cluster center  $c_k$  as the mean of all  $x_i$  that belongs to it.
4. Repeat steps 2-4 until the cluster centers are stable.

K-means clustering is associated with computational expensiveness with respect to the cluster similarity distance measures. Hence a two level EM algorithm is proposed to reduce the effect of excessive computation. The pretenine explanation of EM algorithm is shown below.

## IV. EM ALGORITHM

The EM algorithm is a highly successful tool especially in statistics, but it has also found an array of different applications. One of the more common applications within the statistics literature is for the fitting of linear mixed models or generalized linear mixed models [21]. Another very common application is for the estimation of mixture models. We will show thereafter, the principle of this algorithm.

Given a set of samples  $X = \{x_1, x_2, \dots, x_k\}$ , the complete data set  $S = (X, Y)$  consists of the sample set  $X$  and a set  $Y$  of variables indicating from which component of the mixtures the sample came. We describe, below how to estimate the parameters of the Gaussian mixtures with the EM algorithm.

After classification of the abnormal regions, EM segmentation is adopted to segment the intracranial area in to two clusters which are CSF and brain matter. Basically, EM algorithm is a statistical estimation algorithm used for finding maximum likelihood estimates of parameters in probabilistic models. The procedure to segment the CSF and brain matter

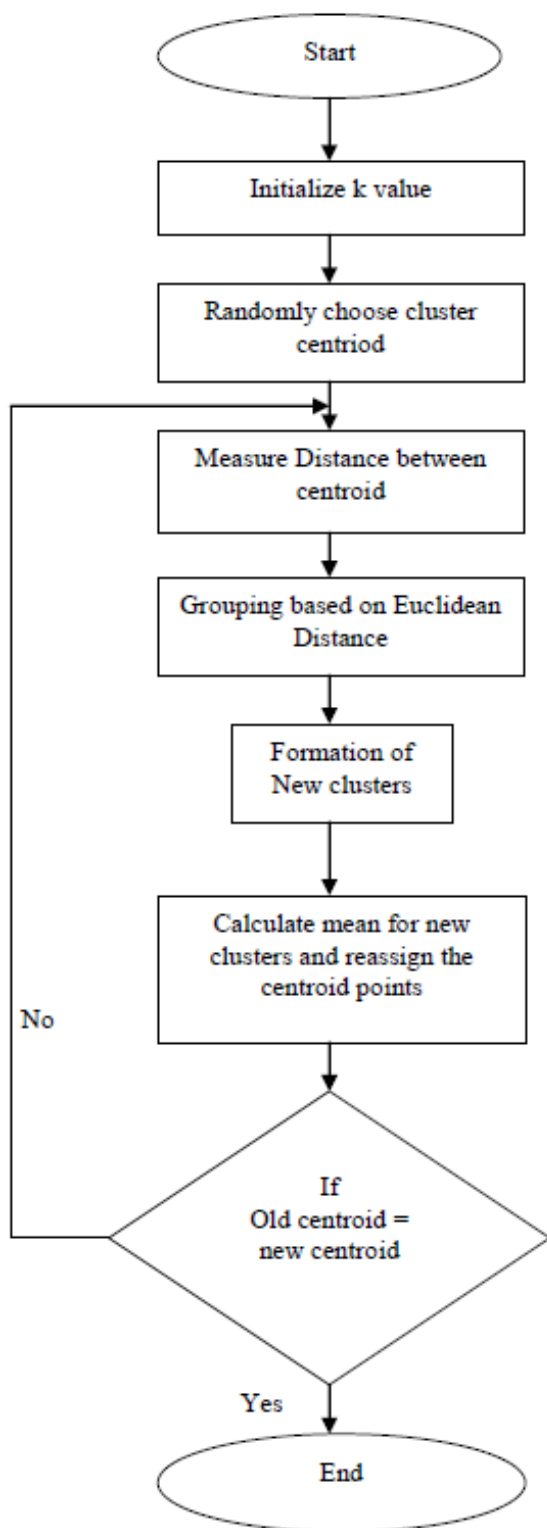


Figure 2:Flow chart for K means Clustering algorithm

work as below:

i) Find the initial values for the maximum likelihood parameters which are means, co variances and mixing weights.

ii) In expectation (E) step, use the probability density function for a Gaussian distribution to compute the cluster probability for every pixel. The multivariate Gaussian conditional density function is written as:

$$f_i(x | \theta_i) = \frac{1}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} \exp[-\frac{1}{2} (x - \mu_i)' \Sigma_i^{-1} (x - \mu_i)] \quad (4)$$

where  $\theta_i = (\mu_i, \Sigma_i)$ .  $x$  is a  $d$ -dimensional feature vector.  $\mu_i$  is the mean vector and  $\Sigma_i$ ,  $|\Sigma_i|$  and  $\Sigma_i^{-1}$  are the  $d$ -by- $d$  covariance matrix, its determinant and inverse respectively.

iii) In maximization (M) step, use the probability values obtained in E-step to re-estimate the means, covariances and mixing weights.

iv) Repeat E-step in (ii) and M-step in (iii).

The algorithm terminates when the difference between the log likelihood for the previous iteration and current iteration fulfills the tolerance.

## V. RESULTS AND DISCUSSION

To study the relative performance of cluster based segmentation methods the following quality measures are calculated. I.Avicibas et.al [24], M.Mrak et.al [23] and A.M. Eskicioglu [22] in their papers have described the statistical image quality measures.

A. Peak signal to noise ratio(PSNR):

$$PSNR = 10 \log \frac{255 * 255}{MSE} dB \quad (5)$$

Where MSE is mean square error [25]. Ideally it is infinity. Practically it is in the range of 25 to 40dB.

B.Average Difference (AD):

$$\sum_{j=1}^M \sum_{k=1}^N \left[ X(j,k) - \hat{X}(j,k) \right] / MN \quad (6)$$

This measure shows the average difference between the pixel values, ideally it should be zero.

C. Structural content (SC), Image Fidelity (IF) and Normalized Correlation Coefficient (NK):

These are the co relational based quality measure which normally look at correlation features between the pixels of original and reconstructed image, they are given as

$$SC = \frac{\sum_{j=1}^M \sum_{k=1}^N X(j,k)^2}{\sum_{j=1}^M \sum_{k=1}^N \hat{X}(j,k)^2} \quad (7)$$

$$IF = 1 - \frac{\sum_{j=1}^M \sum_{k=1}^N \left[ X(j,k) - \hat{X}(j,k) \right]^2}{\sum_{j=1}^M \sum_{k=1}^N \left[ X(j,k)^2 \right]} \quad (8)$$

$$NK = \frac{\sum_{j=1}^M \sum_{k=1}^N \left[ X(j,k) \hat{X}(j,k) \right]}{\sum_{j=1}^M \sum_{k=1}^N \left[ X(j,k)^2 \right]} \quad (9)$$

Normally SC, IF and NK are in the range of 0 to 1, very near to or one is the best.

D. Mean structural similarity index (MSSIM) and Universal Quality Index (UQI):

Zhou Wang et.al[26] in their paper proposed a new quality measures, viz mean structural similarity index and universal quality index. This compares local patterns of pixel intensities that have been normalized for luminance and contrast. It is given by

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (10)$$

Where  $\mu$  and  $\sigma$  are mean and variance respectively, x and y are for original and segmented images. The MSSIM is calculated by taking mean of SSIM and UQI is calculated by substituting the values of  $C_1$  and  $C_2$  as zero.

The quality measures for MRI, X-Ray and Ultrasonic images are calculated and is shown in Table,1 Table2, and Table.3. It is observed that one dB increment of PSNR values in EM models when compare to K-means clustering techniques. Higher Average difference in EM models indicates intra cluster fragileness. Figure 3 and Figure 4 depicts the segmentation of MRI images using K means clustering and EM models respectively. Through the visual identification, we can observe that the edges of segmented MRI images are well preserved in the EM techniques.

## VI. CONCLUSION

In this paper, we consider generic segmentation of the medical images which is carried out for different types of medical images and compared using quality measures such as structural content(SC), Image fidelity(IF), Normalized correlation coefficient(NK),mean structural similarity index(MSSIM) and universal Quality index(UQI). The quality measures like SC, NK, IF and MSSIM are enhanced for the segmented images through the EM models than the K-means clustering algorithms. The future research is in the direction of a comparison of EM models between heuristic MLP and Elman neural network optimization models.

## ACKNOWLEDGEMENTS

The authors thank the Management and Principal, of Bannari Amman Institute of Technology, Sathyamangalam for providing excellent computing facilities and encouragement.

## REFERENCES

1. S. Li, T. Fevens, A. Krzyzak and S. Li Automatic: clinical image segmentation using pathological modeling, PCA and SVM, Engineering Applications of Artificial Intelligence, Volume 19, Issue 4, June 2006, pp. 403-410. .
2. A. Schwaighofer, V. Tresp, P. Mayer, A.K. Scheel and G. Muller, The RA scanner: prediction of rheumatoid joint inflammation based on laser imaging, IEEE Trans. Biomed. Imaging 50 (2003), pp. 375-382.
3. Y. Zheng, H. Li and D. Doermann, Machine printed text and handwriting identification in noisy document images, IEEE Trans. Pattern Anal. Mach. Intell. 26, 2004, pp. 337-345.
4. W.Y. Ma and B. S. Manjunath., 1997. Edge flow; A framework of boundary detection and image segmentation. In: IEEE Conference on Computer Vision and Pattern Recognition, San Juan, Puerto Rico, pp. 744-749.
5. Chenyang Xu. and L.P. Jerry , 1998. Snakes, shapes and gradient vector flow, IEEE trans. Image Process. 73, pp. 359-369.
6. Song Chun Zhu and Alan. Y, 1996, Region competition: Unifying snakes, region growing and Bayes/MDL for multiband image segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 189, pp. 884-900.

7. Gatica-Perez. D and Ruiz Correa, 2001, Extensive partition operators, gray-level connected operators, and region merging/classification segmentation algorithms; Theoretical links. IEEE Trans. Image Process. 109, pp. 1332-1345.
8. Shah.P.K and Udupa.J.K., 2001, Optimum image thresholding via class uncertainty and region homogeneity, IEEE Trans. Pattern Recog. Mach. Intell. 237, pp. 689-706.
9. Jia-Ping Wang, 1998, Stochastic relaxation on partions with connectd components and its application to image segmentation, IEEE Trans. Pattern Anal. Mach. Intell. 206, pp. 619-636.
10. J. Xie, and H. T. Tsui, Image segmentation based on maximum-likelihood estimation and optimum entropy-distribution (MLE-OED), Pattern Recognition Letters, Volume 25, Issue 10, 16 July 2004, pp. 1133-1141.
11. Deng.Y. and Manjunath, B.S., 2001, unsupervised segmentation of color-texture regions in images and video, IEEE Trans. Pattern Anal. Mach. Intell. 238, pp. 800-810.
12. R. Xu, D. Wunsch II, "Survey of clustering algorithms", IEEE Transacions on Neural Networks, 16, 2005, 645-678.
13. A. Jain, M. Murty, P. Flynn, "Data Clustering: A review", ACM Computing Surveys, 31, 1999, 264-323.
14. O. Hall, I. Barak, J.C. Bezdek, " Clustering with a genetically optimized approach", IEEE Trans. Evo. Computation, 3, 1999, 103-112.
15. G. Hamerly, C. Elkan, "Alternatives to the k-means algorithm that find better clusterings", Proc. Of the ACM Conference on Information and Knowledge Management, CIKM-2002, 2002, 600-607.
16. G. H. Omran, A. Salman, A.P. Engelbrecht, "Dynamic clustering using particle swarm optimization with application in image segmentation", Pattern Anal Applic., 8, 2006, 332-344.
17. M. Halkidi, M. Vazirgiannis, I. Batistakis, " Quality scheme assessment in the clustering process". In Proc. Of the 4<sup>th</sup> European Conf. on Principles of Data Mining and Knowledge Discovery, LNCS 1910, 2000, 265-267.
18. M. Halkidi et al., " Clustering validity checking methods: PartII" SIGMOD Rec., 31, No. 3, 2002, 19-27.
19. Stephen J Redmond and Conor Heneghan," A method for initializing the k-means clustering algorithm using kd-trees", Pattern Recognition 28(2007), 965-973.
20. Ujjwal Maulik, Sanghamitra Bandyopadhyay, " Genetic algorithm based clustering technique", Pattern Recognition 33(2000), 1455-1465.
21. Mc. Culloch, C.E, Maximum likelihood algorithm for generalized linear mixed models. Journal of the American Statistical Association, 92, 1997, pp162-170.
22. Ahmet M. Eskicioglu and Paul S. Fisher "Image Quality Measures and their performance" IEEE Transactions on Communications, Vol.43, No.12, December 1995.
23. Marta Mrak, Sonja Grgic and Mislav Grgic " Picture Quality Measures in Image Compression Systems" EUROCON 2003, Ljuijana, Slovenia..
24. Ismail Avicibas, Bulent Sankur, Khalid Sayood " Statistical Evaluation of Image Quality Measures" Journal of Electronic Imaging 11(2), 206-223 (April 2002).
25. N. M. Nasrabadi and R. A. King, " Image coding using vector quantization: A review, "IEEE Trans. Communications, vol.36, no.8,pp. 957-971, August 1988..
26. Zhou Wang, Alan Conrad Bovik., et.al. " Image Quality Assessment: From Error Visibility to Structural Similarity" IEEE Transactions on Image processing, vol. 13, no.4, April 2004.

## AUTHORS PROFILE



**Dr. R. Harikumar** received his B.E (ECE) degree from REC Trichy1988.He obtained his M.E (Applied Electronics) degree from College of Engineering, Guindy, Anna university Chennai in 1990. He was awarded Ph.D. in I&C Engg from Anna university Chennai in 2009. He has 21 years of teaching experience at college level. He worked as faculty at Department of ECE ,PSNA College of

Engineering & Technology, Dindigul. He was Assistant Professor in IT at PSG College of Technology, Coimbatore. He also worked as Assistant Professor in ECE at Amrita Institute of Technology, Coimbatore. Currently he is working as Professor ECE at Bannari Amman



Institute of Technology, Sathyamangalam. He is guiding eight PhD theses in these areas. He has published Thirty papers in International and National Journals and also published around seventy one papers in International and National Conferences conducted both in India and abroad. His area of interest is Bio signal Processing, Soft computing, VLSI Design and Communication Engineering. He is life member of IETE, IEEE and ISTE.



**B. Vinoth kumar** received his B.E (EEE) degree from Bannari Amman Institute of Technology, Sathyamangalam, Bharathiar University, Coimbatore in 2002. He obtained his M.E (Applied Electronics) degree from Government College of Technology, Coimbatore in 2005. He has six year five months of teaching experience at college level. Currently he is working as Assistant Professor (Senior Grade) in Department of EEE at

Bannari Amman Institute of Technology, Sathyamangalam. His area of interest is Medical Image Processing, Soft computing and Embedded systems.



**G. Karthick** received his B.E (ECE) degree from KSR College of Engineering Tiruchengode, Anna University Chennai in 2009. He is pursuing his PG programme in Applied Electronics at Department of ECE, Bannari Amman Institute of Technology Sathyamangalam. His area of interest is Medical Image Processing, Soft computing, Embedded systems and Communication Engineering.



Figure 3.a Segmentation of MRI for K means cluster K=4,



Figure 3.b Segmentation of MRI for K means cluster K=8



Figure 4.a Segmentation of MRI -EM for K=4



Figure 4.b Segmentation of MRI – EM for K=8

Table 1. Quality Measures of MRI Image

BRAIN

K Means							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	31.8547	0.2402	1.0219	0.9834	0.9702	0.9866	0.9865
K=5	33.6507	0.2894	1.0167	0.9855	0.9752	0.9925	0.9924
K=6	34.6035	0.3982	1.0082	0.9885	0.9735	0.9944	0.9944
K=7	37.7329	0.4918	1.0261	0.9895	0.973	0.9973	0.9973
K=8	39.5481	0.5203	1.0078	0.9904	0.9738	0.9984	0.9984
EM							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	33.008	2.4006	0.9762	1.0021	1.0163	0.9777	0.9775
K=5	34.9774	3.0904	0.9574	1.0144	1.0364	0.983	0.9829
K=6	35.2898	1.6348	0.9595	1.0205	0.9972	0.9864	0.9863
K=7	38.5282	0.8514	0.9846	1.004	0.9983	0.9915	0.9914
K=8	39.8584	0.8536	0.9795	1.0074	0.991	0.9926	0.9926

CARDIAC

# Performance Analysis for Quality Measures using K means Clustering and EM Models in segmentation of Medical images

K Means							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	30.6789	0.6718	1.0429	0.9654	0.951	0.9757	0.9755
K=5	31.232	0.5784	1.0274	0.9775	0.9655	0.9843	0.9841
K=6	31.706	0.5762	1.0251	0.9809	0.9676	0.9883	0.9882
K=7	32.0142	0.596	1.0279	0.9807	0.965	0.9901	0.99
K=8	33.8716	0.7574	1.0216	0.986	0.971	0.9941	0.994
EM							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	30.2047	1.3429	1.1069	0.9276	0.8955	0.9565	0.9562
K=5	31.4997	0.9469	1.065	0.9552	0.9311	0.975	0.9748
K=6	31.4648	1.2119	1.0611	0.9598	0.9346	0.9801	0.98
K=7	32.1165	0.8953	1.0401	0.9727	0.9536	0.9861	0.986
K=8	33.0602	0.7351	1.0318	0.9793	0.9613	0.991	0.9909

Table 2. Quality Measures of X-ray image

CHEST

K Means							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	29.296	0.6269	1.0285	0.9784	0.9655	0.9713	0.9712
K=5	30.1746	0.7301	1.0185	0.9864	0.9751	0.9837	0.9836
K=6	30.9338	0.6603	1.0181	0.988	0.9755	0.9885	0.9884
K=7	31.9018	0.7378	1.0136	0.9909	0.9798	0.9916	0.9916
K=8	32.8045	0.6315	1.0134	0.9915	0.9801	0.9933	0.9933
EM							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	29.6805	0.6437	1.0332	0.9749	0.9611	0.9662	0.9659
K=5	30.4526	0.7434	1.018	0.9858	0.9756	0.9805	0.9804
K=6	31.2908	0.349	1.0093	0.9919	0.984	0.9874	0.9873
K=7	32.3736	0.074	1.0035	0.9958	0.9898	0.9912	0.9911
K=8	32.8576	0.2064	1.0046	0.9956	0.9887	0.9924	0.9923

FISH

K Means							
CLUSTERSIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	32.5949	0.5396	1.0233	0.9827	0.971	0.9904	0.9904
K=5	33.6249	0.2311	1.0137	0.9896	0.9804	0.994	0.994
K=6	34.616	0.084	1.0109	0.9921	0.983	0.996	0.996
K=7	35.3317	0.1797	1.0134	0.9907	0.979	0.9971	0.997
K=8	36.2542	0.1094	1.0134	0.992	0.9806	0.9978	0.9978
EM							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	33.1512	0.9766	1.0081	0.9839	0.9858	0.9802	0.9801
K=5	33.6096	0.5768	1.0098	0.9869	0.9842	0.9865	0.9865
K=6	35.1055	0.7175	0.9945	0.998	0.9994	0.9922	0.9922
K=7	35.8457	0.3846	1.0008	0.9965	0.9931	0.995	0.9949
K=8	36.6746	0.1233	1.0069	0.9944	0.987	0.9966	0.9966

Table 3. Quality Measures of Ultrasonic image

BABY

K Means							
CLUSTER SIZE	PSNR	AD	SC	NK	IF	SSIM	UQI
K=4	30.951	0.9019	0.9672	0.989	0.9936	0.8928	0.8882
K=5	31.8368	0.6636	0.966	0.9921	0.9949	0.8923	0.8877

K=6	32.8323	0.6236	0.9647	0.994	0.9962	0.8917	0.887
K=7	33.6023	0.8675	0.9635	0.9937	0.9975	0.891	0.8862
K=8	34.5931	0.6355	0.9622	0.9961	0.9989	0.8901	0.8852
EM							
<b>CLUSTER SIZE</b>	<b>PSNR</b>	<b>AD</b>	<b>SC</b>	<b>NK</b>	<b>IF</b>	<b>SSIM</b>	<b>UQI</b>
K=4	28.6935	4.1371	1.0792	0.9558	0.9217	0.9692	0.9691
K=5	30.0537	2.8927	1.0509	0.9712	0.9467	0.9815	0.9814
K=6	30.6793	2.6808	1.0443	0.9764	0.9527	0.9905	0.9905
K=7	31.2596	2.467	1.0417	0.9782	0.955	0.9931	0.9931
K=8	31.7392	2.6269	1.0414	0.9788	0.9554	0.9949	0.9949

SPINE

K Means							
<b>CLUSTER SIZE</b>	<b>PSNR</b>	<b>AD</b>	<b>SC</b>	<b>NK</b>	<b>IF</b>	<b>SSIM</b>	<b>UQI</b>
K=4	30.3786	0.6163	1.0597	0.9498	0.9338	0.9581	0.9576
K=5	31.3336	0.4186	1.0397	0.9682	0.952	0.9762	0.9759
K=6	32.5776	0.3935	1.0335	0.9759	0.9577	0.9853	0.9851
K=7	33.7688	0.2837	1.0317	0.9792	0.9594	0.9898	0.9897
K=8	34.8629	0.5774	1.0282	0.9825	0.9628	0.993	0.9929
EM							
<b>CLUSTER SIZE</b>	<b>PSNR</b>	<b>AD</b>	<b>SC</b>	<b>NK</b>	<b>IF</b>	<b>SSIM</b>	<b>UQI</b>
K=4	30.3607	1.8747	1.243	0.8441	0.7947	0.8762	0.8746
K=5	30.276	2.3567	1.2202	0.8768	0.8097	0.9316	0.9307
K=6	30.446	2.9812	1.2431	0.8754	0.7946	0.944	0.9433
K=7	31.0315	2.0308	1.1569	0.9143	0.8546	0.9641	0.9636
K=8	31.8322	1.3069	1.0975	0.944	0.9014	0.9775	0.9772