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Segmentation of Natural Images and Retrievals Based On the Mixture of Pearson Type III Distributions

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Abstract: ***In the real world, the image retrievals and image analysis are most important for computer vision and security, surveillances video processing and remote sensing. For authentication and identification an image regional variation are more important. The segmentation of the image plays a vital part in identification of image regions. Among different segmentation techniques of the image, segmentation methods based on a model are prominent and provide accurate results. it is reasonable to consider the probability model, which closely matches with the physical features of image region for describing a suitable model. In the present paper, a novel and new segmentation methods of the image is carried using Type III Pearson system of distributions. In the experimentation one has to assume the image is exemplify with a K-component concoction of Pearson Type III distribution. The EM(Expectation Maximization) algorithm is used to predict the variables of the model. Three images of the real world are arbitrarily chosen from Berkeley database through experimentation. The computed values of VOI, GCE and PRI revealed that proposed method provide more accurate results to same images in which the image regions are left skewed and having long upper tiles. Through image eminence metrics the performance of image retrievals with proposed method is also studied and found that this method performs well then segmentation method based on GMM(Gaussian Mixture Model)..***

Index Terms**:** ***Expectation Maximization(EM), Image segmentation, , Pearson Type III , image eminence metrics.***

I. INTRODUCTION

In image processing, the segmentation of the image places a major part in identifying the different objects and regions. Image segmentation is used to dig out the features or parts or characters of the image in both computer vision and digital image processing (DIP). The characteristic of the digital image includes color, intensity values, textures and reflection features, etc and it also contains histogram features. With the help of image segmentation, one can segregate the digital image into dissimilar non-intersecting sections. Each region is used to identify the object deeply. Image segmentation is used in face recognition, vehicle identification thumb identification and video surveillance. Segmentation of the image is unique research problem in DIP & computer vision .

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One can identify distant characters in different regions of the image. The lot of work is done in image segmentation, literature review also reported regarding the segmentation and its applications by the [1], [2], [3], [4], [5], [6] and [7] are presented different techniques of image segmentation. Segmentation of the image contains two types of methods, 1) model based image segmentation method and 2) heuristic methods. Segmentation methods of the image based on model methods are additional proficient than the heuristic methods of segmentation given by [8], [9]. The segmentation based on model & the segmentation of the image is done based on finite GMM. Much work is reported on Gaussian mixture model [10] and [11]. And it becomes a popular because of its simplicity. In GMM, the regions of image are tacit to be meso- kurtic & symmetric in nature. But [12],[13], [14] and many others developed a different segmentation techniques depending on truncated GMM & new symmetric distribution . The above authors tacit that feature of the regions of the image are symmetric but may not meso-kurtic.

In numerous images, feature vector of image regions are associated with skewed distribution. Basing on the skewed distribution, extremely less exertion is done in the literature concerning the model based segmentation. Hence [15] developed and analyzed segmentation of the image based on Pearson Type I Mixture Distribution. In a few images, the intensities (pixels) of the each part represents the left skewed and asymmetric in nature. Image segmentation methods are empowered and investigated depend on the mixture Pearson Type I and Pearson Type VI [16] distributions through K-means & Hierarchical algorithms, when the pixels of image are left skewed in image regions. But in few images, the pixels of the image parts might not be left skewed. But in few images, might have lengthy higher tail by means of a right slanted curve. To segment such images, one has use right skewed distribution. Therefore, segmentation methods of image are implemented and analyzed with long upper tail and right skewed distributions is capable by the (PTIIID) Pearson Type III distribution. Hence, the pixels of each region and complete image is represented by a finite mixture of PTIIID. Under Bayes framework, the segmentation of the image algorithm is empowered from beginning to end by maximizing component likelihood. By calculating, segmentation recital procedures (PRI, GCE, VOI) by carrying out tests with three images from Berkeley dataset namely BOAT, SEA, WATER & performance is evaluated. The utility of proposed method through image segmentation is match up to with segmentation algorithm based on finite GMM through

K-means algorithm. The effectiveness of the developed model in image recovery is premeditated in the course of computing quality metrics.

II. PEARSON TYPE III MIXTURE DISTRIBUTIONS

The intact digital image is unification of numerous image parts in low-level image examination. The digital images are identified by intensity values in every part. The intensity value $z = f(x, y)$ at a specified position (x, y) is a arbitrary parameter, for the reason the brilliance calculated at a position in the picture is predisposed by different indiscriminate factors similar to wetness, ecological conditions visualization, illumination. Here, the pixels of image region follows a PTIIID to replica the pixels of the water & sky regions. The probability density function (PDF) of intensity values given by

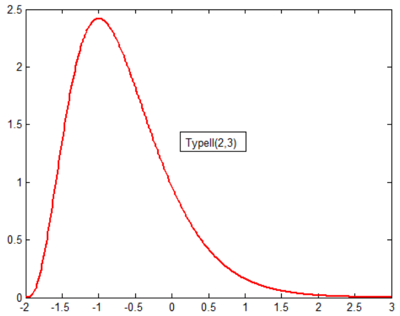
$$f_i(z/a_i,q_i)=\frac{(q_i a_i)^{(q_i a_i+1)}}{e^{q_i a_i} a_i \Gamma(q_i a_i+1)} e^{-q_i z_s}\left(1+\frac{z_s}{a_i}\right)^{q_i a_i}$$

$$-a_i \le z_s < \infty, -\infty \le q_i < \infty \quad (1)$$

Where Γ is a gamma function. For dissimilar standards of the variables, different contours of curves connected with PTIIID are revealed in **Fig** 1. The whole sky and water images are union of image parts are exemplify by PTIIID. Here, the pixel values of complete image follows a K-constituent mixture of PTIIID. The PDF is given by

$$p(z)=\sum_{i=1}^{K}\alpha_i \; f_i(z/a_i,q_i) \quad (2)$$

here, K represents the no of regions of image, $0 \le \alpha_i \le 1$ and $\sum \alpha_i = 1$. α_i is connected by i[th] region in the participate image. In every digital image, the pixel



In every picture, the pixel values are statistically interconnected & these relationship can be abridged by spatial averaging [17] or spatial sampling [18] in different regions of the picture.

III. EVALUATION OF REPLICA PARAMETERS BY ESTIMATION AND MAXIMIZATION.

Using EM [19] algorithm, one can calculate the estimates of replica parameters of the PTIIID. The likelihood of the interpretations $z_1, z_2, \dots, z_N$ pinched from digital image with PDF represented in equation (1).

$$\log L(\theta)=\sum_{s=1}^{N}\log\left[\sum_{i=1}^{K}\frac{\alpha_i (q_i a_i)^{(q_i a_i+1)}}{e^{q_i a_i} a_i \Gamma(q_i a_i+1)} e^{-q_i z_s}\left(1+\frac{z_s}{a_i}\right)^{q_i a_i}\right] \quad (3)$$

The initialization of variables $(a_i, q_i ; i = 1, 2, ..K)$ is the first step of Expectation Maximization algorithm and the constituent values $(\alpha_i ; i = 1, 2, \dots, K)$ are calculated from the experimental values. In order to calculate the Maximum likelihood (ML) estimates of unidentified variables $\theta = (a_i, q_i, \alpha_i; i = 1, 2, \dots, K)$, one has to use EM algorithm iteratively.

A. EXPECTATION-STEP

Here, the anticipation value of logarithm of $L(\theta)$ through the primary inconsistent vector $\theta^{(0)}$ is $Q(\theta;\theta^{(0)}) = E_{\theta^{(0)}}[\log L(\theta)/\bar{z}]$ the primary parameters $\theta^{(0)}$, the density of intensity value z_s calculated using

$$p(z_s,\theta^{(l)})=\sum_{i=1}^{K}\alpha_i^{(l)} f_i(z_s,\theta^{(l)}),\; L(\theta)=\prod_{s=1}^{N} p(z_s,\theta^{(l)})$$

This entails

$$\log L(\theta)=\sum_{s=1}^{N}\log\left(\sum_{i=1}^{K}\alpha_i f_i(z_s,\theta^{(l)})\right) \quad (4)$$

In any region K , the conditional probability of any inspection z_s is given by

$$t_k(z_s,\theta^{(l)})=\left[\frac{\alpha_k^{(l)} f_k(z_s,\theta^{(l)})}{p(z_s,\theta^{(l)})}\right]$$

The expectation (E) of the logarithm likelihood utility of model from the heuristic influence of Jeff A. Bilmes (1998) given by

$$Q(\theta;\theta^{(l)})=\sum_{i=1}^{K}\sum_{s=1}^{N}\left(t_i(z_s,\theta^{(l)})\left(\log f_i(z_s,\theta^{(l)})+\log\alpha_i^{(l)}\right)\right) \quad (5)$$

B. MAXIMIZATION-STEP

The assessment of model parameters are obtained by maximizing the $Q(\theta;\theta^{(l)})$ with $\sum \alpha_i = 1$. The above can unraveled by constructing the first order Lagrange function,

$$S=\left[E(\log L(\theta^{(l)}))+\lambda\left(1-\sum_{i=1}^{K}\alpha_i^{(l)}\right)\right] \quad (6)$$

here, λ is Lagrangian constant. To maximize, one can combine the constraint with the log likelihood function.

Hence, $\frac{\partial S}{\partial \alpha_i}=0$ This implies $\sum_{i=1}^{N}\frac{1}{\alpha_i}t_i(z_s,\theta^{(l)})-\lambda=0$

Summation on both sides for all observations, then λ = N as a result $\hat{\alpha}_i = \frac{1}{N}\sum_{s=1}^{N} t_i(z_s,\theta^{(l)})$. The reorganized equation (α_i) for $(l+1)$[th] identicalness given by

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$$\alpha_i^{(l+1)} = \frac{1}{N}\sum_{s=1}^{N} t_i(z_s,\theta^{(l)}) = \frac{1}{N}\sum_{s=1}^{N}\left[\frac{\alpha_i^{(l)} f_i(z_s,\theta^{(l)})}{\sum_{i=1}^{K}\alpha_i^{(l)} f_i(z_s,\theta^{(l)})}\right] \quad (7)$$

To renew the parameters a_i, q_i, i = 1, 2, …, K , calculate the derivative of $Q(\theta;\theta^{(l)})$ with q_i, a_i & equal to zero.

Therefore $\frac{\partial}{\partial a_i}Q(\theta;\theta^{(l)})=0$ imply $E\left[\frac{\partial \log L(\theta;\theta^{(l)})}{\partial a_i}\right]=0$

The renew equation for a_i at $(l+1)^{th}$ continuance given as

$$a_i^{(l+1)} = \sum_{s=1}^{N}\frac{t_i(z_s,\theta^{(l)})}{\left[\frac{q_i^{(l)}z_s}{a_i^{(l)}+z_s}+q_i^{(l)}\Gamma\left(q_i^{(l)}a_i^{(l)}+1\right)-q_i^{(l)}\log\left(q_i^{(l)}a_i^{(l)}\left(a_i+z_s\right)\right)\right]t_i(z_s,\theta^{(l)})} \quad (8)$$

The modernize equation for q_{i1} at $(l+1)^{th}$ continuance given

$$q_i^{(l+1)} = \frac{\sum_{s=1}^{N} q_i\left[a_i^{(l)}\Gamma(q_i^{(l)}a_i^{(l)}+1)+(a_i^{(l)}+z_s)-a_i^{(l)}\log\left(q_i^{(l)}a_i^{(l)}\left(\frac{z_s+a_i^{(l)}}{a_i^{(l)}}\right)\right)\right]}{a_i^{(l)}\sum_{s=1}^{N}t_i(z_s,\theta^{(l)})}-1 \quad (9)$$

IV. INITIALIZATION OF MODEL VARIABLES

EM algorithm is derived through renew equations of model variables. The MME (moment method of estimation) and heuristic segmentation algorithms such as K-means are used for the initialization of the parameters. By estimating the parameters, one can estimate the effectiveness of EM, which is deeply reliant on dissimilar regions of the digital image and it drawn by identifying the pixel intensities of image (plotting histogram). In EM, the combination variable α_i & the model variables such as a_i , q_i respectively are known as apriori. By picking a arbitrary sample from the total image is generally used process for initializing parameters [20]. By considering the heavily increased computational time and large sample size, the performance of the method can be increased. A few regions might not be trial correctly, whenever size of the sample is small. It can surmount by using K–Means, which divides complete digital image into dissimilar identical parts. The centers of each group are recalculated, when pixel links to a new group in K – Means.

V. SEGMENTATION ALGORITHM

The variables are refined by means of EM. The primary step in segmentation algorithm, to allocate the intensity values to different image fragments. There are four steps, which are presented in algorithm and they are

Step 1: By maneuverings histogram of each picture element in picture.

Step 2: Using K-Means, one can acquire the first approximation of the model and instant approximation for every section as confer in above section IV.

Step 3: Using EM algorithm, acquire the renew approximations of replica variables q_i, a_i and α_i for i=1,2,3,..,K through the renew calculated equation known by (8) & (9) correspondingly in section III.

Step 4: allocate every picture element into the consequent j^{th} segment basing on the ML of the jth constituent L_j.

$$L_j = \max_{j\in k}\left[\frac{(q_j a_j)^{(q_j a_j+1)}}{e^{q_j a_j}a_j\Gamma(q_j a_j+1)}e^{-q_j z_s}\left(1+\frac{z_s}{a_j}\right)^{q_j a_j}\right],$$

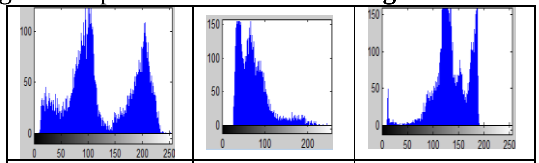
$$-a_i \le z_i < \infty \,, -\infty < q_j < \infty.$$

VI. EXPERIMENT RESULTS

The accomplishing of segmentation technique developed for natural images on the earth. To execute, moment method of estimations is used for initializing the model parameters. For initial division of the feature vector into different segmented regions, one used non-parametric techniques of segmentation namely K-means.

A. Initialization of Parametrs By K-Means Algorithm

The three images which are required for conducting the experiment are acquired from Berkeley dataset. Segmentation of image is carried out on the images such as BOAT, SEA, WATER. A mixture of PTIIID is assumed to be followed by the pixels (feature) of the image. Therefore the image encloses with K sections and pixels in each section (region) of image pursue a PTIIID with dissimilar variables and regions are identified by histograms of the image. The histograms of pictures are revealed in **Fig** 2.



BOAT	SEA	WATER

Fig 2. DIFFERENT IMAGE HISTOGRAMS

The first approximation of the image sections K in every picture are acquired & specified in Table 1.

TABLE I. Initial Approximation Of K

Name of the picture	BOAT	SEA	WATER
Estimate of K	**3**	**3**	**4**

From the above Table, the images BOAT AND SEA has three peaks(segments) and images WATER has four peaks (segments). The first & final estimate of the model variables q_i, a_i & α_i where i = 1, 2,3,4…,K , for every picture region are calculated with the equations in section III. The following table contains calculated values of initial and final parameters by EM.

Table II. Anticipated Values Of The Variabless For BOAT

Parameters	Values of Primary Variables			Values of Final Variables By EM		
	Region			Region		
	1	2	3	1	2	3
α_i	0.3	0.3	0.3	0.3	0.3	0.3

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a_i	192	-63.2	74.3	1.17E-06	-7.08	0.45
q_i	0.1	0.09	-0.31	853276	-0.23	0.43

Table III. Anticipated Values Of The Variables For SEA

Parameters	Values of Primary Variables			Values of Final Variables By EM		
	Region			Region		
	1	2	3	1	2	3
α_i	0.33	0.33	0.3	0.33	0.33	0.3
a_i	107.2	92.1	36.6	1.455	81.10	0.4
q_i	-0.107	0.001	-0.1	0.125	0.0024	2.2

Table IV. anticipated Values Of The Variables For WATER

Parameters	Values of Primary Variables				Values of Final Variables By EM			
	Region				Region			
	1	2	3	4	1	2	3	4
α_i	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
a_i	21	-30	31	-24	-45	-6.5	1.2	-3.2
q_i	0.1	0.1	-0.1	-0.03	0.3	-0.5	-0.3	0.2

By deputing the final approximations of the variables, the PDF of pixels of every picture is calculated. The calculated PDF & segmentation algorithm mentioned in Above section V, the segmentation of image is ready for the three pictures below contemplation. The Real & segmented pictures are given below.

ORIGINAL IMAGES	SEGMENTED IMAGES

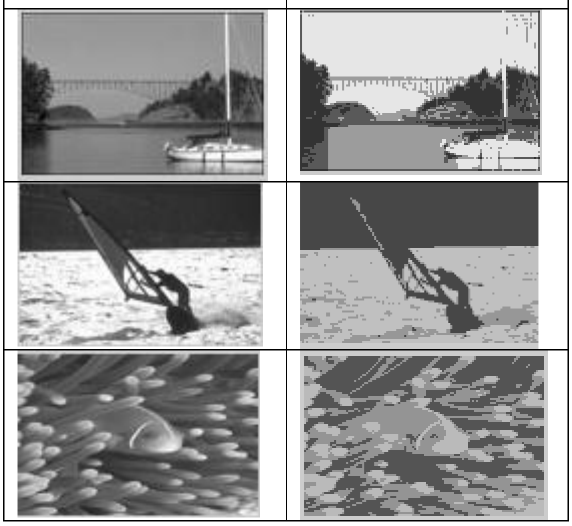


Fig 3. Original and Segmented Images

VII. PERFORMANCE EVALUTION

There are three recital values are utilized to calculate the recital evaluation of segmentation algorithm and they are (i) PRI(probabilistic rand index) given by R. Unnikrishnan, C. Pantofaru, M. Hebert [21] (ii) VOI (variation of information) by Unnikrishnan (2007) and (iii) GCE (global consistence error). The recital of Segmentation algorithm is tested by calculating the segmentation recital values for three images with PRI, VOI& GCE. The computed values are contrast with earlier developed finite GMM with K-Means. The comparative study is presented in Table VI.

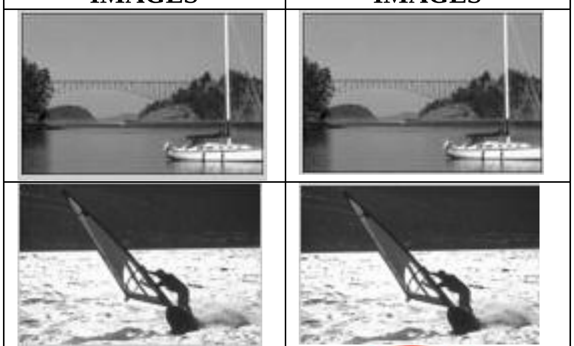
Table V. Segmentation Performance Values

IMAGES	**TECHNIQUE**	**PERFORMACE VALUES**		
		PRI	**GCE**	**VOI**
BOAT	GMM	0.881	0.675	8.458
	PTIIID-K	0.884	0.682	8.12
SEA	GMM	0.893	0.781	8.412
	PTIIID-K	0.920	0.764	8.224
WATER	GMM	0.010	0.097	6.775
	PTIIID-K	0.011	0.081	6.750

Here three images are considered for experimentation & examined that PRI standards of the future segmentation algorithm has upper values than finite GMM using K-means. The GCE & VOI standards of anticipated segmentation method have lesser values than the finite GMM with K-means. From the above results the anticipated algorithm has better values then the existing algorithm defected on the finite GMM with K-Means.

By mounting the segmentation technique, it is necessary to verify the efficacy of segmentation in model structure of the picture for picture recovery. The recital valuation of the recovered picture calculated using skewed picture eminence testing. The purpose of picture eminence testing techniques are frequently used since the results of an intent assess consent to a reliable assessment of diverse techniques. At present, numerous picture eminence values presented for recital estimates of the image segmentation technique. Study of eminence results is specified by [22]. To test recital valuation of the empowered segmentation technique, the subsequent image eminence equations. The calculated PDFs of the images under contemplation the recovered images are acquired & given in **Fig** 4.The image eminence values are calculated for three recovered images BOAT, SEA, WATER by the anticipated technique & GMM through K-means and the values specified below.

NOVEL IMAGES	RECOVERED IMAGES



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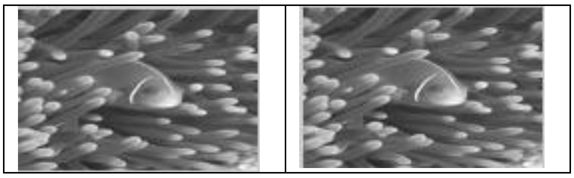

Fig 4. The Novel and Recovered Images

Table VI. Proportional cram of Image eminence Measures

IMAGE	Eminence Measures	GMM	PTIIID-K
BOAT	AD	0.9545	0.8259
	MD	1	1
	IF	0.9568	0.9605
	MSE	0.6584	0.5624
	SNR	6.8524	10.9467
	IQI	1	1
SEA	AD	0.8845	0.87542
	MD	1	1
	IF	0.9999	0.9999
	MSE	0.8549	0.3744
	SNR	5.8964	13.7892
	IQI	0.3598	0.4360
WATER	AD	0.7942	0.72563
	MD	1	1
	IF	0.8973	0.9034
	MSE	0.4582	0.2871
	SNR	5.8597	13.29736
	IQI	0.5048	0.6844

From the above values, picture eminence values of three pictures are summiting the standard values. Consequently, by the anticipated technique the pictures are recovered precisely. After measuring all eminence measures, it is examined that the recital of the projected technique in recovering the images is superior than the finite GMM.

VIII. CONCLUSION

From the cram, it is examined that the values acquired for the PTIIID mixture method with K-means are superior than the values acquired from GMM through K-means.
Still there is scope to expand and investigate image segmentation algorithms stand on feature vector with additional features such as brightness, saturation, hue angle etc., using multivariate Pearson mixture distributions.

REFERENCES

1. Srinivas Y, K.Srinivasa Rao, P.V.G.D.Prasad Reddy, "Unsupervised image segmentation using generalized Gaussian distribution with hierarchical clustering, Journal of advanced research in computer engineering, Vol.4, No.1, 2010, pp. 43-51.
2. Pal N.R & Pal S.K. , "A Review On Image Segmentation Techniques", Pattern Recognition, Vol.26, No.9, 1993,pp. 1277-1294.
3. Cheng, "Color Image Segmentation: Advances and Prospects" Pattern Recognition, Vo1.34, 2001,pp. 2259-2281.
4. Mantas Paulinas and Andrius Usinskas ,"A survey of genentic algorithms applications for image enhancement and segmentation", Information Technology and control, Vol.36, No.3, (2007), pp. 278-284.
5. Jahne ," A Practical Hand Book on Image segmentation for Scientific Applications, CRC Press, 1995 .
6. Shital Raut, "Image segmentation- A State-Of-Art survey for Prediction", International conference on Adv. Computer control, 2009,pp.420-424.
7. Srinivas Y., "Unsupervised Image Segmentation based on Finite Doubly Truncated Gaussian Mixture model with K-Means algorithm", International Journal of Physical Sciences, Vol. 19, 2007, pp. 107-114.
8. P Chandra Sekhar, K.Srinivasa Rao, M Seshasaee, Text independeny speaker identification model using pearsonian system of models and k –means algorithm, journal of innovation in computer scienceengineering,Vol.3(2),jan 2014, pp 29-33.
9. Nasios N. and Bors A.G. ,"Variational learning for Gaussian Mixtures", IEEE Transactions on Systems, Man and Cybernetics, Part B : Cybernetics, Vol.36(4), 2006, pp. 849-862.
10. Srinivas Yerramalle And K.Srinivasa Rao, Unsupervised image classification using finite truncated Gaussian mixture model, Journal of Ultra Science for Physical Sciences, Vol.19, No.1, 2007, pp 107-114.
11. K. Srinivasa Rao, P. Chandra Sekhar & P. Srinivasa Rao, " Image Segmentation for Animal Images using Finite Mixture of Pearson type VI Distribution", Global Journal of Computer Science and Technology: Graphics & Vision Volume 14 Issue 3 Version 1.0,2014 pp.1-12 .
12. P.Chandra Sekhar, K.Srinivasa Rao & P.Srinivasa Rao,"Image Segmentation Algorithm for Images having Asymmetrically Distributed Image Regions", International Journal of Computer Applications (0975 – 8887) Volume 96– No.21, 2014, pp 64-73.
13. Lei T,"Performance Evaluation of Finite Normal Mixture Model –Based Image Segmentation Techniques", IEEE Transactions On Image Processing, Vol-12, No.10, 2003, pp. 1153-1169.
14. Jeff A. Bilmes, "A Gentle Tutorial of the EM Algorithm and its Application to Parameter Estimation for Gaussian Mixture and Hidden Markov Models" International Computer Science Institute Berkeley CA, 94704,1998.
15. Mclanchan G. and Peel D.,"The EM Algorithm For Parameter Estimations ", John Wiley and Sons, New York, 2000.
16. Eskicioglu M.A. and Fisher P.S.,"Image Quality Measures and their Performance", IEEE Transactions On Communications, Vol.43, No.12, 1995 , pp.2959-2965.
17. Paulinas and Andrius Usinskas ,"A survey of genentic algorithms applications for image enhancement and segmentation", Information Technology and control, Vol.36, No.3, (2007), pp. 278-284.
18. Meila ,"Comparing Clustering – An axiomatic view", in proceedings of the 22nd International Conference on Machine Learning, 2005, pp. 577-584.
19. Rose H. Turi," Cluster Based Image Segmentation", Ph.d Thesis, Monash University, Australia,2001.
20. Yamazaki T., "Introduction Of EM Algorithm Into Color Image Segmentation", Proceedings of ICIRS'98, pp. 368-371.
21. R. Unnikrishnan C. Pantofaru M. Hebert, "A Measure for Objective Evaluation of Image Segmentation Algorithms" IEEE, The Robotics Institute Carnegie Mellon University, 2005.
22. Marr D."Theory of Edge Detection" Proceedings of Royal Society London, B207, 1980,pp. 187-217.

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