ISSN (Online) : 2319 - 8753
ISSN (Print) : 2347 - 6710

International Journal of Innovative Research in Science, Engineering and Technology

Volume 3, Special Issue 3, March 2014

2014 International Conference on Innovations in Engineering and Technology (ICIET'14)
On 21st & 22nd March Organized by

K.L.N. College of Engineering, Madurai, Tamil Nadu, India

Image Segmentation Using Unsupervised Techniques

B.M.Nagarajan[#1], G.Prem paul[#2], P.Senthil babu[#3]

#1Department of Electronics and Communication Engineering, K.L.N. College of Engineering, Pottapalayam, Sivagangai, Tamilnadu, India

#2Department of computer Science Engineering, K.L.N. College of Engineering, Pottapalayam, Sivagangai, Tamilnadu, India

#3 Department of Electronics and Communication Engineering, K.L.N. College of Engineering, Pottapalayam, Sivagangai, Tamilnadu, India

ABSTRACT— Unsupervised Techniques of segmentation are simple and the segmented output using these techniques gives the best results. This paper presents an automatic segmentation method based on unsupervised segmentation done on Ultrasound (US) images received from the radiologist. US imaging is widely used in clinical diagnosis and image-guided interventions, but suffers from poor quality. One of the most important problems in image processing and analysis is segmentation. US image is difficult to segment due to low contrast and strong speckle noise. Here we present three unsupervised techniques, namely thresholding,
K-means clustering and expectation maximization and compare their results. The uniqueness of this paper is that EM technique is used for texture featured image which gives far better results of segmentation.

KEYWORDS— medical ultrasound images, segmentation, thresholding, k-means clustering, expectation maximization.

I. Introduction

Image segmentation is the process of partitioning an image into disjoint homogeneous regions so that all pixels in a region are similar with respect to some characteristics such as color, intensity, or texture, while adjacent regions are significantly different with respect to the same characteristics. Segmentation is one of the essential low-level vision operations with a fundamental role in the final result of higher-level operations such as object recognition and tracking, image retrieval, face detection, etc. Clearly, color images contain much more information than gray-level ones, which can be used to improve the quality of segmentation.

Although this improvement is obtained at the expense of computational complexity, it is no longer a major problem with the recent increase in processing power. Accordingly, in this paper, we consider color image segmentation problem.

In recent years, considerable efforts have been made in computer-aided diagnosis (CAD) of medical images which gives doctors and researchers a platform for detail analysis of these images. Segmentation is a process of dividing an image into regions having similar properties such as gray level, color, texture, brightness, contrast etc. The techniques available for segmentation of images can be broadly classified into two classes: (I) based on gray level – the methods used here are (a) amplitude segmentation methods based on histogram features (b) edge-based segmentation (c) region based segmentation and (II) based on textural feature. For some typical applications, particularly in the medical image processing, segmentation based on gray level does not give the desired results; in such applications, segmentation based on textural feature methods gives more reliable results; therefore, texture-based analysis is extensively used in analysis of medical images.

II. SYSTEM OVERVIEW

In our work, we propose for segmentation of ultrasound Image, three unsupervised segmentation techniques, namely Image segmentation through k–means clustering algorithm, Segmentation using thresholding and image segmentation using Expectation Maximization (EM) Algorithm. All these Techniques were used for texture featured US image. EM Method of segmentation done after feature extraction by Gabor filters gives good segmentation results. In this method, Multi-channel filtering, namely Gabor filters are used for texture analysis to capture important information from the image.

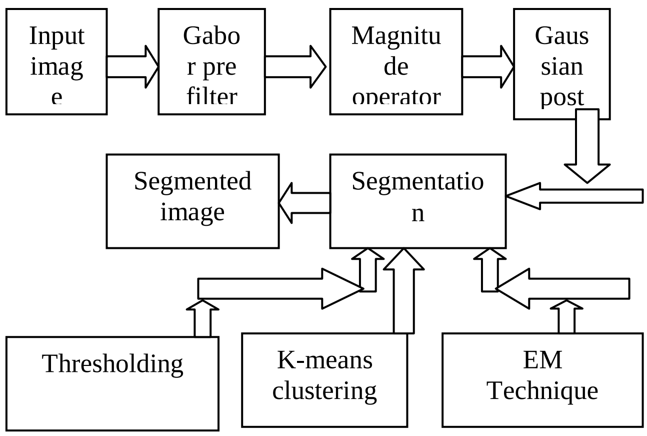


Fig.1 Block Diagram of unsupervised segmentation

III. RELATED WORK

2-D Gabor filter is a popular tool in medical image classification [8], texture analysis and discrimination. The process of texture segmentation using Gabor filters[12] involves a proper filter bank design that should be tuned to different spatial-frequencies and orientations to cover the spatial frequency space, decomposing the image into a number of filtered images; feature extraction from these images, and clustering of the pixels in the feature space to produce segmented image. On generating texture features using multichannel filters two primary issues must be addressed. The first issue deals with the functional characterization of the channels as well as their number, orientation and spacing.

The second issue deals with extracting significant features by data integration from different channels. Texture segmentation requires simultaneous measurements in both the spatial and the spatial frequency domains. Filters with smaller bandwidths in the spatial frequency domain are more desirable as they allow us to do fine distinctions.

A Gaussian filter is a filter whose impulse response is a Gaussian function. Gaussian filters have the properties of having no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. It is considered the ideal time domain filter, just as the sinc is the ideal frequency domain filter.

IV. PROPOSED ALGORITHM

4.1. *Thresholding*

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that the thresholds are derived from the radiographs instead of the (reconstructed) image.

Categorizing thresholding Methods

- Histogram shape-based methods, where, for example, the peaks, valleys and curvatures of the smoothed histogram are analyzed
- Clustering-based methods, where the gray-level samples are clustered in two parts as background and foreground (object), or alternately are modeled as a mixture of two Gaussians
- Entropy based methods result in algorithms that use the entropy of the foreground and background regions, the cross-entropy between the original and binarized image, etc.
- Object Attribute-based methods search a measure of similarity between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence, etc. arg min
- Spatial methods [that] use higher-order probability distribution and/or correlation between pixels
- Local methods adapt the threshold value on each pixel to the local image characteristics.

Multiband thresholding

Color images can also be thresholded. One approach is to designate a separate threshold for each of the RGB components of the image and then combine them with an AND operation. This reflects the way the camera works and how the data is stored in the computer, but it does not correspond to the way that people recognize color. Therefore, the HSL and HSV color models are more often used. It is also possible to use the CMYK color model.

4.2. K-means clustering

K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. K-means clustering aims to partition observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Verona cells.

The problem is computationally difficult (NP-hard) however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are similar to the expectation maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

Description

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets ($k \leq n$)$\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS):

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \left\| \mathbf{x}_j - \boldsymbol{\mu}_i \right\|^2$$

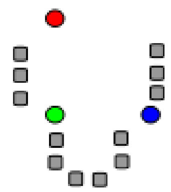
Where $\boldsymbol{\mu}_i$ is the mean of points in S_i.

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

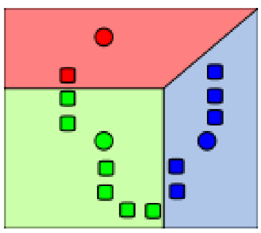
1. Pick K cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster centre. The difference is typically based on pixel colour, intensity, texture and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

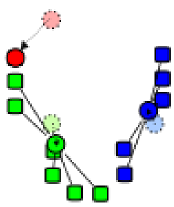
Demonstration of the standard algorithm

- 

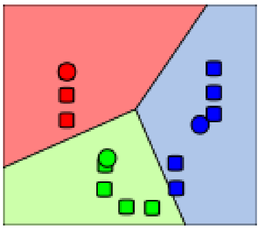
1) K initial "means" (in this case=3) are randomly generated within the data domain (shown in colour).

- 

2) K clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

- 

3) The centroid of each of the k clusters becomes the new mean.

- 

4) Steps 2 and 3 are repeated until convergence has been reached.

As it is a heuristic algorithm, there is no guarantee that it will converge to the global optimum, and the result may depend on the initial clusters. As the algorithm is usually very fast, it is common to run it multiple times with different starting conditions. However, in the worst case, k-means can be very slow to converge: in particular it has been shown that there exists certain point sets, even in 2 dimensions, on which k-means takes exponential time, to converge. These point sets do not seem to arise in practice: this is corroborated by the fact that the smoothed running time of k-means is polynomial.

4.3. *Expectation Maximization (EM) Algorithm*

Expectation maximization (EM) algorithm is an iterative method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

EM Introduction

The EM algorithm is used to find the maximum likelihood parameters of a statistical model in cases where the equations cannot be solved directly. Typically these models involve latent variables in addition to unknown parameters and known data observations. That is, either there are missing values among the data, or the model can be formulated more simply by assuming the existence of additional unobserved data points.

The EM algorithm proceeds from the observation that the following is a way to solve these two sets of equations numerically. One can simply pick arbitrary values for one of the two sets of unknowns, use them to estimate the second set, then use these new values to find a better estimate of the first set, and then keep alternating between the two until the resulting values both converge to fixed points. It's not obvious that this will work at all, but in fact it can be proven that in this particular context it does, and that the derivative of the likelihood is (arbitrarily close to) zero at that point, which in turn means that the point is either a maximum or a saddle point

Although EM iteration does increase the observed data (i.e. marginal) likelihood function there is no guarantee that the sequence converges to a maximum likelihood estimator. For multimodal distributions, this means that an EM algorithm may converge to a local maximum of the observed data likelihood function, depending on starting values. There are a variety of heuristic approaches for escaping a local maximum such as random restart

EM is particularly useful when the likelihood is an exponential family: the E step becomes the sum of expectations of sufficient statistics, and the M step involves maximizing a linear function.

EM is frequently used for data clustering in machine learning and computer vision. In natural language processing, two prominent instances of the algorithm are the Baum-Welch algorithm (also known as forward-backward) and the inside- outside algorithm for unsupervised induction of probabilistic context-free grammars.

Filtering and Smoothing EM Algorithms

A Kalman filter is typically used for on-line state estimation and a minimum-variance smoother may be employed for off-line or batch state estimation. However, these minimum-variance solutions require estimates of the state-space model parameters. EM algorithms can be used for solving joint state and parameter estimation problems.

E-Step

Operate a Kalman filter or a minimum-variance smoother designed with current parameter estimates to obtain updated state estimates.

M-*Step*

Use the filtered or smoothed state estimates within maximum-likelihood calculations to obtain updated parameter estimates.

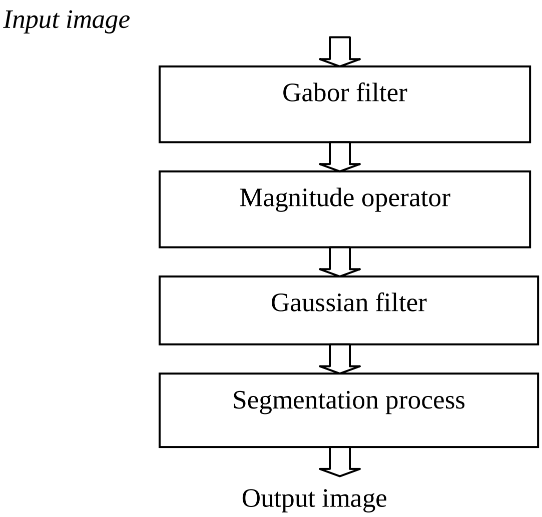


Fig.2 Flow diagram of Unsupervised Techniques

5.1. *Gabor filter*

Gabor filter is a linear filter used for edge detection and extraction of texture features; it is used a lot in character recognition and fingerprint enhancement. Gabor features extract local pieces of information which are then combined to recognize an object or region of interest. On generating texture features using multichannel filters two primary issues must be addressed. The first issue deals with the functional characterization of the channels as well as their number, orientation and spacing. The second issue deals with extracting significant features by data integration from different channels

5.2 *Magnitude operator*

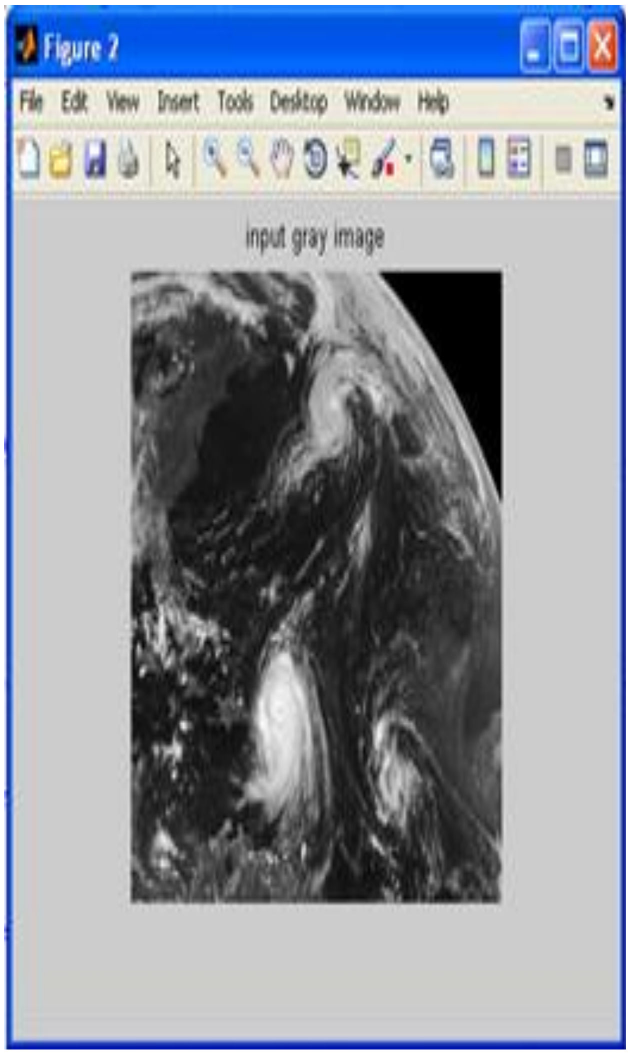
It is used to find out the maximum pixel size of image and also it modifies or change input image according to the format of Gaussian post filter.

5.3 *Gaussian filter*

A Gaussian filter is a filter whose impulse response is a Gaussian function. Gaussian filters have the properties of having no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. It is considered the ideal time domain filter, just as the sinc is the ideal frequency domain filter.

SIMULATION RESULTS

Fig.3 Input image



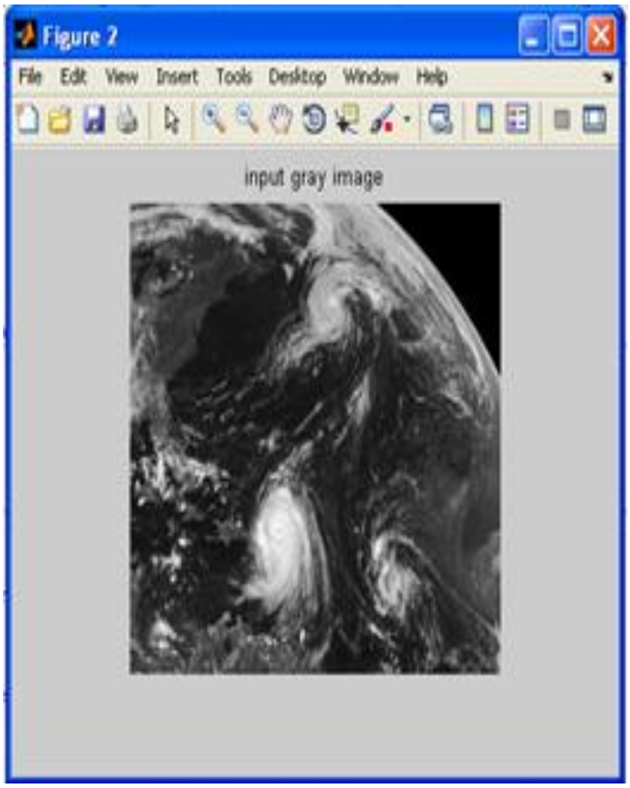


Fig. 4 Grey scale image

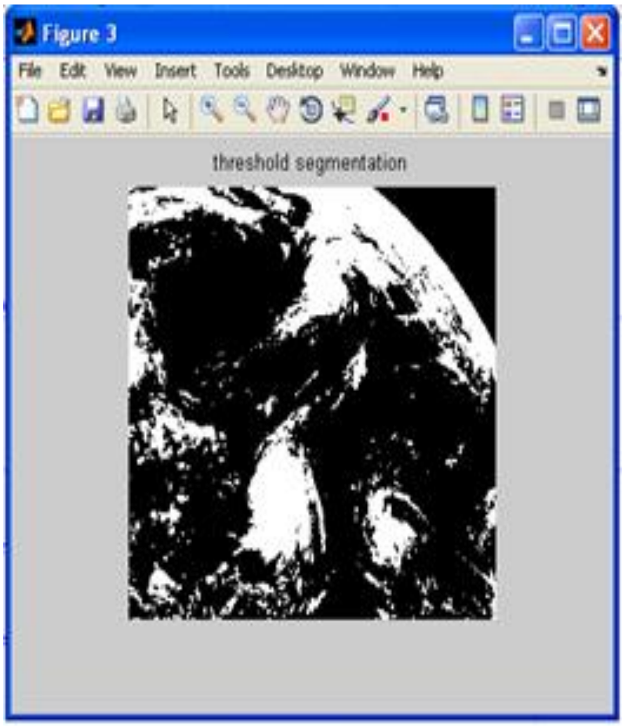


Fig. 5 Threshold Segmentation Output

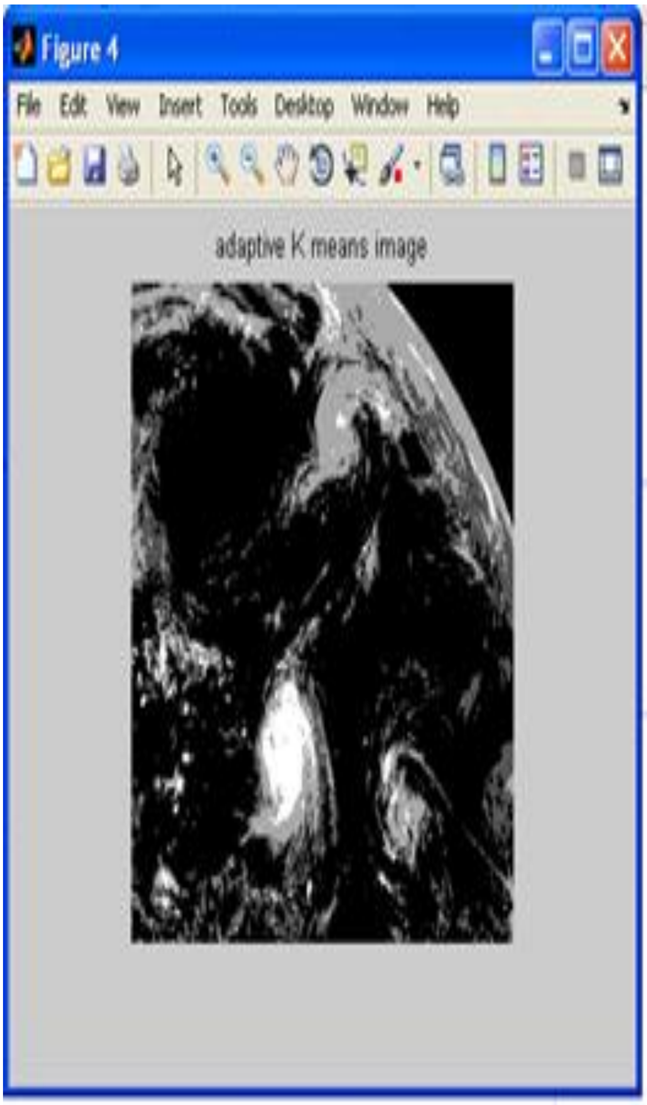


Fig.6 Adaptive K means segmentation output

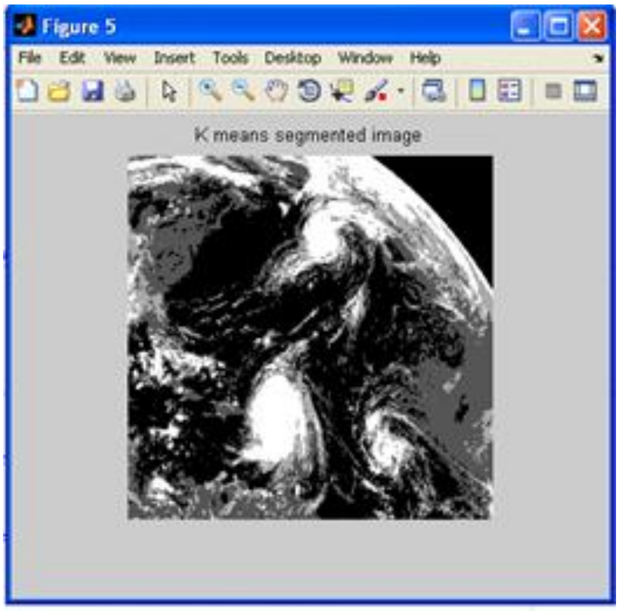


Fig.7 K means clustering segmentation output

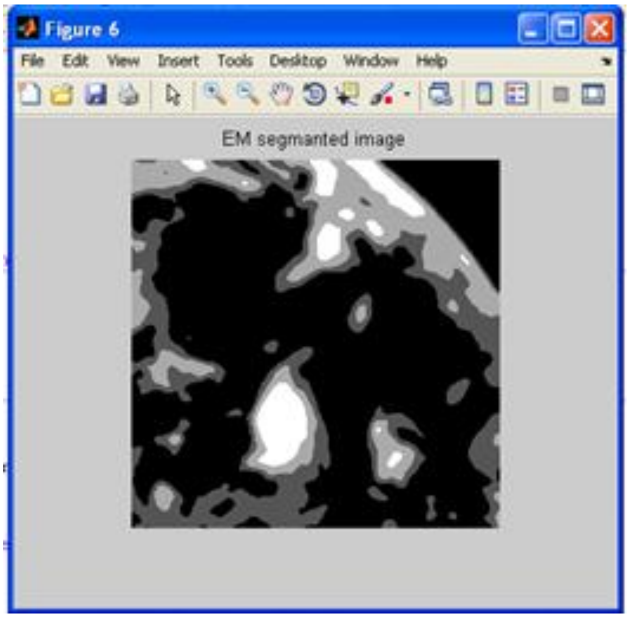


Fig. 8 EM output

VI. Conclusion

Here I propose three techniques namely thresholding, K-means clustering and Expectation Maximization for segmentation are used on texture featured images. These techniques are used to segment US images received from radiologist. In the preprocessing stage, images are smoothened by Gaussian filter which suppresses the variations in the texture features within the same texture. At the end of the feature extraction step we are left with a set of feature images extracted from the filter outputs. Pixels that belong to the same texture region have the same texture characteristics, and should be close to each other in the feature space. The filtered images were subjected to Thresholding, K-means clustering and EM Techniques for segmentation, the result of which is shown. K-means is able to detect liver and GB but the background is not clear. Segmentation using EM algorithm shows that the boundary of the image is well defined and this methodology is able to detect the liver and cyst quite well. The segmented output using EM Algorithm gives the best results. This method can be applied on various other US images to detect cysts and tumors.

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