ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 5, August 2013

COMPARISON OF EM ALGORITHM WITH A GUASSIAN MULTIRESOLUTION ALGORITHM FOR MRI SEGMENTATION

H.A.Wani[1], K.P.Jadhav[2]

Assistant Prof., KCE'S COE&IT, Jalgaon(M.S.), India[1]

Assistant Prof., KCE'S COE&IT, Jalgaon (M.S.), India[2]

Abstract: Segmentation of anatomical regions of brain is fundamental problem in medical image analysis. In general, segmentation is process in which object is divided into its constituents parts. In this paper, MRI of brain is divided into its constituent's parts which may be used for medical diagnosis purpose. Consequently we used statistical approach to segment the brain image. Using this approach, we proved Gaussian multiresolution algorithm gives better result than EM algorithm under the variance. We know that EM algorithm fails to utilize the strong spatial correlation between pixels but this drawback is eliminated by combining Gaussian multiresolution algorithm with the EM algorithm. Finally Gaussian multiresolution EM algorithm displays the high powerful technique which keeps the advantage of EM algorithm and remove the drawback of EM algorithm.

Keywords: MRI, Image segmentation,EM algorithm,GMEM Algorithm,Matlab

I.INTRODUCTION

Magnetic resonance imaging is primarily a non-invasive medical imaging technique used in radiology to visualize detailed internal structure and limited function of the body. MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) does, making it especially useful in neurological (brain), musculoskeletal, cardiovascular, and oncological (cancer) imaging. Unlike CT, MRI uses no ionizing radiation. Rather, it uses a powerful magnetic field to align the nuclear magnetization of hydrogen atoms in water in the body. Radio frequency (RF) fields are used to systematically alter the alignment of this magnetization. This causes the hydrogen nuclei to produce a rotating magnetic field detectable by the scanner. This signal can be manipulated by additional magnetic fields to build up enough information to construct an image of the body Magnetic resonance imaging is a relatively new technology.

This paper deals with MR image segmentation algorithm based on the conventional Expectation Maximization (EM) algorithm and multi resolution analysis of images. Although EM algorithm was used in MRI brain segmentation, as well as, image segmentation in general, it fails to utilize the strong spatial correlation between neighboring pixels. The multi resolution-based image segmentation techniques, which have emerged as a powerful method for producing high-quality segmentation of images, are combined here with the EM algorithm to overcome its drawbacks and in the same time take its advantage of simplicity. In this paper some data sets are used to test the performance of the EM and the proposed Gaussian Multi resolution EM (GMEM) algorithm. The results, which proved more accurate segmentation by the GMEM algorithm compared to that of the EM algorithm, are represented statistically and graphically to give deep understanding.

II.THE EM ALGORITHM

The EM algorithm produces Maximum Likelihood (ML) estimates of parameters when there is a many-to-one mapping to the distribution governing the observation. The EM algorithm is used widely in the image segmentation field and it produces very good results especially with a limited noise level. The image is considered as a Gaussian mixture model. Each class is represented as a Gaussian model and the pixel intensity is assumed as an observed value of this model. The EM is used for finding the unknown parameters of the mixture model [2].

The EM algorithm consists of two major steps: an expectation step (Estep), followed by a maximization step (M-step). The expectation step is to estimate a new mapping (pixel-class membership function) with respect to the unknown underlying variables, using the current estimate of the parameters and conditioned upon the observations. The maximization step then provides a new estimate of the parameters. These steps iterate until convergence is achieved.[2]

2.1 *EM Algorithm Steps*

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

IJIREEICE

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 5, August 2013

1. The number of classes K and the Image I are provided to the system.
2. The initial estimation of parameter Φ(0) is estimated based on the histogram of the image and the number of classes.
3. Performing the E-step and M-step iteratively until convergence, at each iteration the E-step compute the class probability of each pixel based on the current estimation of Φ(t). M-step computes the new expectation of Φ(t+1) based on values computed in the previous E-step. After convergence the maximum estimator of Φ is produced.
4. Use ΦML in a classifier to generate the classification matrix C
5. Assign color or label to each class based on the classification matrix C and generates the segmented image.

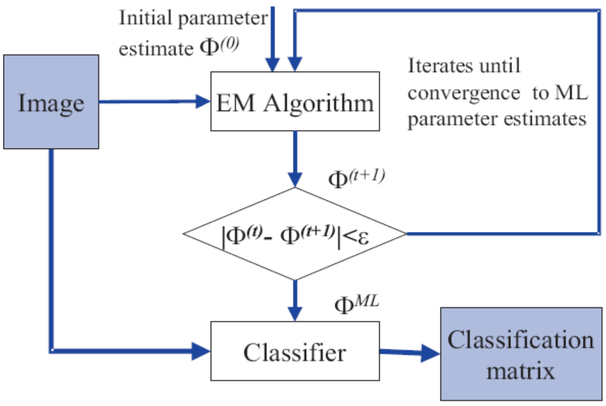

Fig.1 EM Algorithm Steps

III. THE DRAWBACKS OF THE EM ALGORITHM

Although the EM algorithm is used in MRI of human brain segmentation, as well as image segmentation in general, it fails to utilize the strong spatial correlation between neighboring pixels. For example, if a pixel, i, all its surrounding pixels, neighbor pixels, are being classified to belong to the same class say Ka, but if it has an intensity closer to the mean of another class, say Kb, the classifier would incorrectly classify this pixel to belong to class Kb.

This drawback is due to that the EM is based on The the GMM which assumes that all the pixels distributions are identical and independent; however it has an advantage that it reduces the computational complexity of the segmentation task by allowing the use of the well-characterized Gaussian density function [1].

IV. THE GMEM ALGORITHM

In this paper we propose a new image segmentation algorithm, namely; Gaussian Multi resolution EM algorithm, GMEM, which is based on the EM algorithm and the multi resolution analysis of images. It keeps the advantages of the simplicity of the EM algorithm and in the same time overcome its drawbacks by taking into consideration the spatial correlation between pixels in the classification step. We mean by the term "spatial correlation", that the neighboring pixels are spatially correlated because they have a high probability of belonging to the same class. We think that utilizing the spatial correlation between pixels is the solution key to overcome the drawbacks of the EM algorithm. Therefore, we propose to modify the EM algorithm so that it takes in its consideration the effect of the neighbor pixels when classifying the current pixel, by utilizing the multi resolution technique.

4.1 *Multiresolution technique*

The multi resolution-based image segmentation techniques, which have emerged as a powerful method for producing high-quality segmentations of images, are combined here with the EM algorithm to overcome the EM drawbacks and in the same time take its advantages. The Multi resolution analysis is based on the aspect that "all the spaces are scaled versions of one space", where successive coarser and coarser approximations to the original image are obtained. This is interpreted as representing the image by different levels of resolution. Each level contains information about different features of the image. Finer resolution, i.e., higher level, shows more details, while coarser resolution, i.e., lower level, shows the approximation of the image and only strong features can be detected. Working with the image in multi resolution enables us to work with the pixel as well as its neighbors, which makes the spatial correlation between pixels easy to implement. In this work we have generated two successive scales of the image, namely, parent and grandparent images. We used an approximation filter, in particular, a Gaussian filter, to generate such low resolution images. The Gaussian filter is a low pass filter used to utilize the low frequency components of neighboring pixels . We used the Gaussian filter in a manner similar to a moving window. Where a standard Gaussian filter of size n x n is created and in the same time the original image is divided into parts each of which has the same size as the filter size. The filter is then applied to each part of the image separately. This can be interpreted as a windowed convolution where the window size is the same as the filter size. and also this agree with the concept of the distinct block operation where the input image is processed a block at a time. That is, the image is divided into rectangular blocks, and some operation is performed on each block individually to determine the values of the pixels in the corresponding block of the output image, the

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

IJIREEICE

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 5, August 2013

operation in our case is the Gaussian filter. Each time we apply the filter on a part of the image the result is placed as a pixel value in a new image in a similar location to that where it was obtained. Later we use this new image as the parent of the original image. The classification of the parent or grandparent represent the approximated class of these pixels together. The implementation of the GMEM algorithm, therefore, is done as follows: we apply the EM algorithm on both the parent and grandparent images to produce three segmented images in three successive scales of the original image.

4.2 *GMEM Algorithm steps*

1.Start with an image Io as input and generates its parent I1 and grandparent I2 using the Gaussian moving windows of sizes 3x3 and 5x5, respectively.

2. Apply the conventional EM algorithm for image segmentation on the images Io, the parent I1, and the grandparent I2. The outputs of this step are the classification matrices C0, C1, and C2 respectively.

3.Reclassify the original image I. using the weights specified previously to generate the final classification matrix C. That represents the classification of the image I0 after taking into account the spatial correlation between pixels.

4. Assign colors or labels to each class and generates the segmented images.

V.IMPLEMENTATION

Implementation of this work is done using matlab software.

Implementation steps are as follows

5.1 *Image Segmentation steps*

1.Read and load the Images.
2.Convert the RGB Image into Gray Image
3.Plot histogram of Image
4. Make one separate figure window.
5. Use the subplot command to create axes in tiled position and show the image on figure window.
6. Give the title to the original image and histogram of the image.
7. Assign the number of classes.
8. Give the means of classes in row matrix form and also give variance.

5.2 *EM Algorithm Expectation Process*

1. Equalize the pixel probability of each class and display it.
2. Decide the size of image ie.206 * 179.
3. Convert the 2D image into 1D image i.e. Conversion of image into only row matrix form.
4. Take the transpose of row matrix.
5. Also take the transpose of mean which is row form i.e. Convert into column form.
6. Mixer- rectification of image.
7. Distribution of each pixel based on its probability, mean and standard derivation

5.3Em Algorithm Maximization Process

8. It computers the new expectation of parameter vectors based on values computed in previous E step.
1. Converge the E step and M step.
2. Give the white background to four figure window
3. Provide colors to segmented output.
4. Integrate all the j segmented output.

5.4 *GMEM Algorithm*

1. Load the image
2. Read the image
3. Convert RGB image into gray scale image.
4. Plot the histogram of the image
5. Apply 3×3 gaussian filter to original image
6. Apply 5×5 gaussian filter to the original image
7. Assign classes
8. Assign mean values
9. Repeat EM algorithm

5.5 *Graphical user Interface*

1. Create the GUI.

VI. EXPERIMENTAL RESULTS

In order to test the performance ,and good comparisons between the EM algorithm and GMEM algorithm introduced in this paper ,we use following number of images, we get the following results:

Image 1 Image 2 Image 3

Fig.2 Brain MRI Images as input.

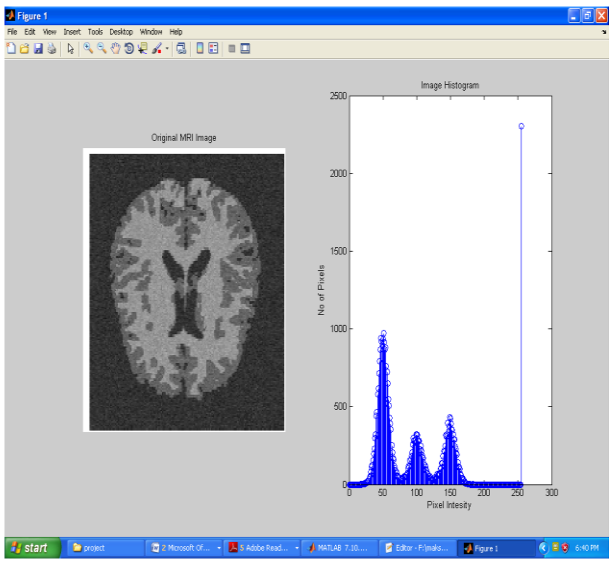

Fig.3 Histrogram for image 3

This is result of EM algorithm under the variance 100

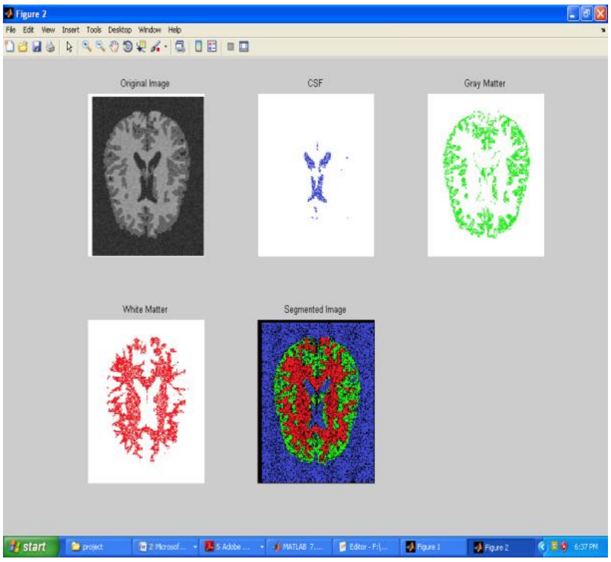

Fig.4 Segmented EM Output for image 3 under the variance 100

This is result of Gaussian multiresolution under the variance 100.

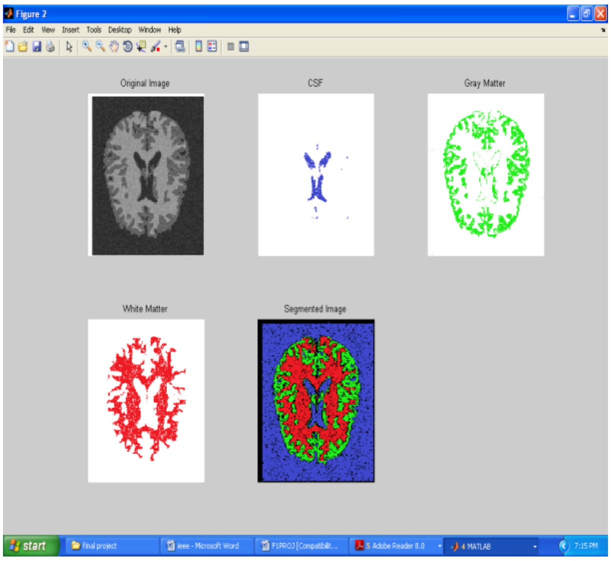

Fig.5 Segmented GMEM Output for image 3 under the variance 100

AT VARIANCE =100

Table 1. Various Parameters of MR Images at Variance 100

IMAGE TESTED	WM	GM	CSF	EM (MSE)	GMEM (MSE)
IMAGE 1	13.25	47.5	0.78	12.3	18.17
IMAGE 2	12.7	36.6	8.53	12.6	23.46
IMAGE 3	43.7	38.36	5.71	12.52	38.62

Result of EM algorithm under the variance 300

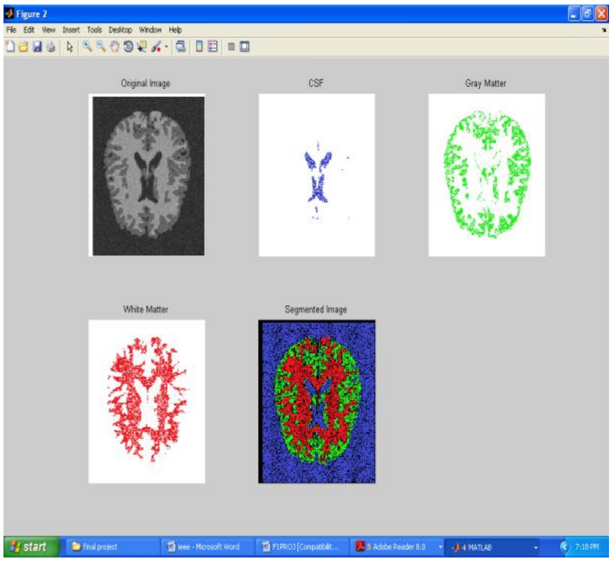

Fig.6 Segmented EM Output for image 3 under the variance 300

Result of GMEM algorithm under the variance of 300:

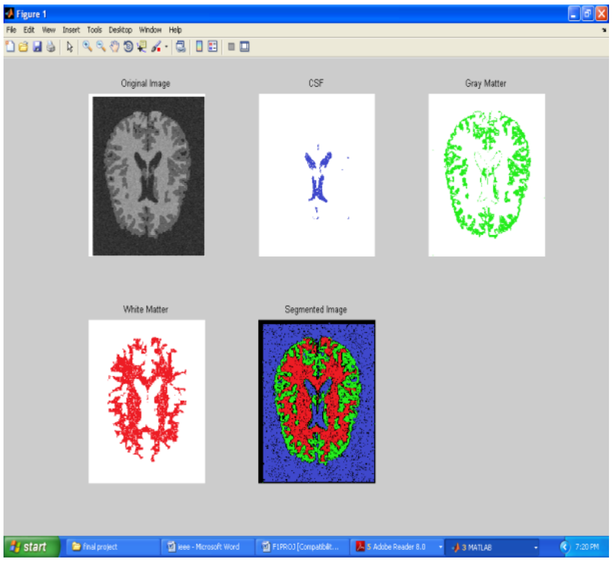

Fig.7 Segmented GMEM Output for image 4 under the variance 300

AT VARIANCE=300

Table 2. Various Parameters of MR Images at Variance 300

IMAGE TESTED	WM	GM	CSF	EM (MSE)	GMEM (MSE)
IMAGE 1	13.25	47.5	0.78	12.6	20.12
IMAGE 2	12.7	36.6	8.53	12.8	24.46
IMAGE 3	43.7	38.36	5.71	12.92	39.62

VII. CONCLUSION

A new multiresolution algorithm for image segmentation has been proposed in this paper, namely, the Gaussian multiresolution EM algorithm (GMEM). The proposed

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 5, August 2013

algorithm is based on the conventional EM algorithm, the multiresolution analysis. EM prevailed many other segmentation techniques because of its simplicity and performance. However it is found to be very sensitive noise level where a drop of mean square error reduces when noise increased from low to high levels, at variance 100 and 300. To overcome this drawback the GMEM algorithm uses the multiresolution analysis enables the algorithm to utilize the spatial correlation between neighboring pixels. The GMEM algorithm uses Gaussian filter and distinct block operation to generate low resolution images from the original images.

REFERENCES

[1] Mohammed F. Tolba, Mostafa G. Mostafa Tarek, F. Gharib, Mohammed A-Megeed [1] ,"MR-brain image segmentation using Gaussian Multi resolution analysis and the EM algorithm".
[2] [DLR97] Dempster, A. P.; Laird, N. M.; Rubin, D. B.: Maximum likelihood from incomplete data via the EM algorithm. In: Journal of Royal Statistics Society, volume 38-B:pp. 1–38, 1997.
[3] Saeed, Mohammed: Maximum Likelihood Parameter Estimation of Mixture Models and Its Application to Image Segmentation and Restoration. Ph.D. thesis, Department of Electrical Engineering and Computer Science, Massachusetts Institute ofTechnology, 1997.
[4] Alirezaie, J.; Jernigan, M.E.; Nahmias, C.: Neural networkbased segmentation of magnetic resonance images of the brain.In: IEEE Transactions on Nuclear Science, volume 44(2):pp.194–198, April 1997.
[5] Bonet, Jeremy S. De: Multiresolution sampling procedure for analysis and synthesis of texture images. In: SIGGRAPH '97: Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques, pp. 361–368. ACM Press/Addison-Wesley Publishing Co., New York, NY, USA, 1997.
[6] Castleman, Kenneth R.: Digital Image Processing. Prentice Hall, Inc., 1996.
[7] Cavallaro, A.; Gelasca, E.D.; Ebrahimi, T.: Objective evaluation of segmentation quality using spatio-temporal context. In: ICIP02, pp. III: 301–304. 2002.
[8] Gonzalaz, Rafael G.; Woods, Richard E.: Digital Image Processing. Addision-Wesley publishing Co, 1993.
9] Gonzalez, Rafael C.; Woods, Richard E.: Image Processing Toolbox, 5th Edition. The Mathworks. Inc., 2005.
[10] Olson, Clark F.: Maximum-likelihood image matching. In: IEEE Trans. Pattern Anal. Mach. Intell., volume 24(6):pp.853–857, 2002.
[11] Pal, N.R.; Pal, S.K.: A review on image segmentation techniques. In: PR, volume 26(9):pp. 1277–1294, September 1993.
[12] Rosenfeld, A.: Some useful properties of pyramids. In: Multiresolution Image Processing and Analysis, pp. 2–5. Springer-Verlag, 1984.[Ros84b] Rosenfeld, Azriel, editor:
[13] Saeed, Mohammed: Maximum Likelihood Parameter Estimationof Mixture Models and Its Application to Image Segmentation and Restoration. Ph.D. thesis, Department of Electrical Engineering and Computer Science, Massachusetts Institute ofTechnology, 1997.
[14] Salem, Mohammed A-Megeed; Tolba, M. F.; Mostafa, M. G.; Gharib, T. F.: MR-brain image segmentation using Gaussian multiresolution analysis and the EM algorithm. In: ACMIEEE 8th International Conference Of Enterprise Intelligent Computing, volume 2, pp. 165–170. France, April 23-26 2003.
[15] Tood, A.; Moon, K.: The expectation maximization algorithm.In: IEEE Signal Processing Magazine, pp. 47–68, November 1996.
[16] Types of Medical Imaging www.suite101.com › Health & Wellness › General Medicine
[17] en.wikipedia.org/wiki/Medical imaging
[18] Medical Imaging Primer, www.medicalimaging.org
[19] Image processing toolbox, www.Mathworks.com
[20] Signal Processing toolbox, www.Mathworks.com
[21] MATLAB 7.5 help