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A New Multiresolution Algorithm for Image Segmentation

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ABSTRACT - The current literature on MRI segmentation methods is reviewed. Particular emphasis is placed on the relative merits of single image versus multispectral segmentation, and supervised versus unsupervised segmentation methods. Image pre-processing and registration are discussed, as well as methods of validation. In this paper, we present a new multiresolution algorithm that extends the well-known Expectation Maximization (EM) algorithm for image segmentation. The conventional EM algorithm has prevailed many other segmentation algorithms because of its simplicity and performance. However, it is found to be highly sensitive to noise. To overcome the drawbacks of the EM algorithm we propose a multiresolution algorithm which proved more accurate segmentation than the EM algorithm.

Keywords: Maximization, segmentation, pixel-based, Gaussian Mixture

1. INTRODUCTION

Magnetic resonance imaging (MRI) represents the intensity variation of radio waves generated by biological systems when exposed to radio frequency pulses [1][2]. A Magnetic resonance image (MRI) of the human brain is divided into three regions other than the background, white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) or vasculature [2]. Because most brain structures are anatomically defined by boundaries of these tissues classes, a method to segment tissues into these categories is an important step in quantitative morphology of the brain. An accurate segmentation technique may facilitate detection of various pathological conditions affecting brain parenchyma, radiotherapy treatment and planning, surgical planning and simulations, and three-dimensional (3-D) visualization of brain matter for diagnosis and abnormality detection [2]. Image segmentation is to divide the image into disjoint homogenous regions or classes, where all the pixels in the same class must have some common characteristics. According to the nature of the image the approach of segmentation may be either region-based approaches [3][4], or pixel-based approaches, where the segmentation is done according to the pixels features, such as pixel intensity [5][6][7][8]. A will known approach of image segmentation based on pixel intensity is the Expectation Maximization (EM) algorithm [9][10], which is used to estimate the parameters of different classes in the image. To overcome the drawbacks of the EM algorithm, we propose a multiresolution algorithm, the Gaussian Multiresolution EM algorithm, GMEM, which proved high reliability and performance under different noise levels, and in the same time it keeps the advantages of the conventional EM algorithm.

2. IMAGE SEGMENTATION AND EM ALGORITHM

Image segmentation is one of the most important stages in artificial vision systems. It is the first step in almost every pattern recognition process. In some context other terms like object isolation or object extraction are used. Image segmentation is computationally the division of an image into disjoint homogeneous regions or classes. All the pixels in the same class must have some common characteristics. The conventional segmentation procedure starts by transforming the original image into a feature space in order to find the boundaries between the different classes. It is followed by a mapping step, which assigns a label to each pixel such that all the pixels of the same features will have the same class.

2.1. PIXEL-BASED APPROACHES

In the pixel-based approaches the properties of single pixels are used to identify the class to which the pixel belongs. The used properties are mainly the pixel intensity or the intensities of the closed neighborhood of the pixel. The segmentation is done regardless of the position of the pixel in the image or of the characteristics of the structure of the object. That means if two pixels have similar intensities they will be assigned most probably to the same object or class even if they are in separated parts of the image.

2.2. EM ALGORITHM

The EM algorithm was explained and given its name in a classic 1977 paper by Arthur Dempster, Nan Laird, and Donald Rubin.[1] In statistics, an expectation-maximization (EM) algorithm is a method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. EM is an iterative method which alternates between performing an expectation (E) step, which computes the expectation of the log-likelihood, evaluated using the current estimate for the latent variables, 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.

The EM algorithm for image segmentation based on modeling the image as a Gaussian Mixture Model, GMM, where, the parameters of the model are not knowing a prior (Missing data), and it utilize the estimation theory to use the pixel intensity (incomplete data) to estimate the Missing data [10][11].

2.2.1. STATISTICAL METHODS.

The Expectation Maximization (EM) algorithm was developed and employed independently by several different researchers until Dempsters et al. [DLR97] brought their ideas together, proved convergence, and coined the term "EM algorithm". Since that seminal work hundreds of papers employing the EM algorithm in many areas have been published. Generally, 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. A set of observed data $X = \{xi \mid i = 1, ..., N\}$ can be modeled as to be generated from a mixture of random processes $X1, X2, ..., XK$, with joint probability distribution $f(X1, X2, ..., XK)$, where K is the number of classes or distribution functions present in the mixture. It is usually assumed that these processes represent independent identically distributed random variables. Then one can write:

$$f(X_1, X_2, \ldots, X_K) = \prod_{k=1}^{K} f(x, \theta_k)$$

where $f(x,$ _$k)$ 8k = 1, 2, ...,K is the probability distribution function of the random variable Xk, and _k = $\{\mu k,$ _$k\}$ stands for the parameters that define the distribution k.

ɸ = $\{p1, ..., pK, \mu 1, ..., \mu K,$ _1, ..., _$K\}$

is called the parameter vector of the mixture, where pk are the mixing proportions

(0 _ pk _ 1, 8k = 1, ...,K, and$\sum k\, pk = 1$).

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 [TM96].

1. THE E-STEP:

Compute the expected value of $z_{i\ k}$ using the current estimate of the parameter vector ɸ was introduced in [Sae97]:

$$z_{i,k}^{(t)} = \frac{p_k^{(t)} G(x_i \mid \theta_k^{(t)})}{f(x_i \mid \Phi^{(t)})}$$

Where $z_{i,k}$ is the probability of xi belonging to class k, where $1 \leq i \leq N$, $1 \leq k \leq K$ and xi is the intensity value of the pixel i. It should be referenced afterwards as the pixel xi.

$z_{i,k}$ satisfies the conditions:

$i)\ 0 \leq z_{i,k} \leq 1$

$ii)\ \sum_k z_{i,k} = 1$

$iii)\ \sum_i z_{i,k} > 0.$

$G(x_i \mid \theta_k^{(t)})$ is the probability of pixel x_i given it is a member of class k.

p_k is the class proportional in the model $\sum_k p_k = 1$.

The $f(x_i \mid \Phi)$ is the total probability function that is defined as:

$$f(x_i \mid \Phi) = \sum_{k=1}^{K} p_k G(x_i \mid \theta_k^{(t)})$$

The superscript (t) means the iteration number t.

2. THE M-STEP:

Use the data from the expectation step as if it were actually measured data and compute the mixture parameters as introduced in [Sae97]:

$$\mu_k^{(t+1)} = \frac{\sum_{i=1}^{N} z_{i,k}^{(t)} x_i}{\sum_{i=1}^{N} z_{i,k}^{(t)}}$$

$$\sigma_k^{2(t+1)} = \frac{\sum_{i=1}^{N} z_{i,k}^{(t)} (x_i - \mu^{(t+1)})^2}{\sum_{i=1}^{N} z_{i,k}^{(t)}}$$

$$p_k^{(t)} = \frac{\sum_{i=1}^{N} z_{i,k}^{(t)}}{N}$$

The EM algorithm starts with an initial guess ɸ(0) of the parameters of the distributions and the proportions of the distributions in the image. It iterates until a conversion of the parameter vector ɸ is achieved. Fig. 1 shows its flowchart

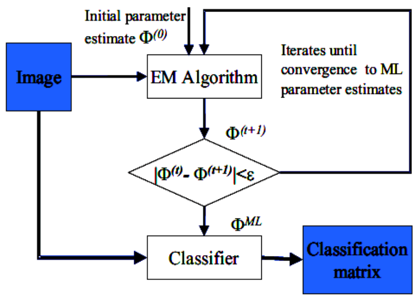


Figure Block diagram of the EM algorithm. I: input image. S: segmented image.

The EM algorithm is always followed by a classification step. The EM is producing the missing parameters in _, which are then used by a classifier Which is defined as?

$$k_i = \operatorname*{argmax}_k (G(x_i \mid \theta_k^{(t)}))$$

It assigns a class membership to a pixel i depending on its intensity xi to the class whose parameter vector maximizes the Gaussian density function. The value of this membership function is placed in a new matrix called *classification matrix*. It is a matrix that has the same size as the image and the same dimensions. The values of the matrix elements represent the classes of the pixels of the corresponding image. The EM algorithm is used in different image segmentation problems, such as medical images, natural scene images, and texture images. The authors in [CD00] presented an enhancement segmentation of texture images by the EM algorithm. The basic idea behind their algorithm is to minimize the expected value of the number of misclassified pixels by EM estimates using the Maximization of the Posterior Marginal's (MPM) of the classification. After each iteration of the EM algorithm the MPM uses the estimated parameters to maximize the conditional probability of the classification of a certain pixel given its observed value.

3. THE GAUSSIAN MULTIRESOLUTION EM ALGORITHM

In this paper we propose a new image segmentation algorithm, namely; Gaussian Multiresolution EM algorithm, GMEM, which is based on the EM algorithm and the multiresolution 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 multiresolution technique

3.1. THE MULTIRESOLUTION ANALYSIS.

The multiresolution-based image segmentation techniques, which have emerged as a powerful method for producing high-quality segmentation of images [5][8], are combined here with the EM algorithm to overcome the EM drawbacks and in the same time to take its advantages. The Multiresolution analysis is based on the aspect that "all the spaces are scaled versions of one space" [14], 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 multiresolution 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 [15]. 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 [16], 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 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.

In the following we illustrate this in more details. In Fig. 1, the original image I_0 at scale J=0, say of size 9x9 is divided into parts each part of size 3x3, then a Gaussian filter of size 3x3 is applied to the first part of the image $I_0(1:3,1:3)$ the result of the windowed convolution, say a_{11}, is placed in location (1,1) in the new image, I_1. This step is repeated to each part of the image which generate a sequence of coefficients, $a_{11}..a_{13}$, $a_{21}..a_{23}$, and $a_{31}..a_{33}$, these coefficients are placed in the new image by the same order as they obtained. The new created image isof size 3x3 represents a lower-resolution approximation of the original image and acts as a parent image, at scale J=1, of the original image I_0, at scale J=0, where each nine neighboring pixels in I_0 are used to generate one pixel in I_1. By the same way, we used a Gaussian filter of size 5x5 to create the grandparent image I_2 from I_0 at scale J=2. Generally, the distinct block operation may require image padding, since the image is divided into blocks. These blocks will not always fit exactly over the image. In this work we used the symmetric padding where the boundaries of the image at which the image is padded are replicated [17].

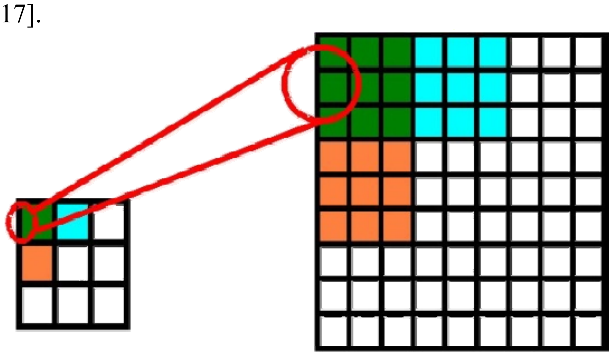


Fig: 2. Illustration of the use of the Gaussian-window

3.2 MULTIRESOLUTION IMGAE SEGEMENTATION

Once the parent and grandparent images have been created, we move to the next step by solving the segmentation problem using the different scales of the image. Saeed and Karl [5] made three assumptions while they were trying to solve the segmentation problem using multiresolution analysis of image. Those assumptions are, first, the pdf of pixel (x, y) at resolution J is dependent upon its neighbors, second, it is dependent upon the parent pixel (x ,y) at resolution J+1 and its neighbors, third, it is dependent upon the grandparent pixel (x ,y) at resolution J+2 and its neighbors. Thus, their model attempted to utilize the dependence of pdf across both scale and space towards the aim is to modify the Gaussian Mixture density goal of a more robust segmentation algorithm. Their function such that they penalize the likelihood of pixel membership to a certain class when its neighbors, parent, and parent's neighbors have a low probability of belonging to this same class [5]. We tried different approaches to utilize the multiresolution image analysis with the conventional EM algorithm. Thus, we did not use the assumptions in [5], instead we made another assumption that "the classification of a pixel (x,y) at resolution J is dependent upon both the classification of its parent pixel (x',y') at resolution J+1 and the classification of its grandparent pixel (x ,y) at resolution J+2". We made this assumption because we think that the parent and grandparent pixels represent the averaging of the interested pixel and its neighbors. So, the classification of the parent or grandparent represents 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. In other words, we used the EM algorithm to segment the image of each scale independent on the others. The EM algorithm is followed by a classifier, therefore, the output of this step is three classification matrices C_0, C_1, and C_2 representing the segmentation of the original image, its parent, and its grandparent images, respectively. Those matrices, obtained from the segmentation of the different resolutions of the image are then used to find the final classification of the image. The final classification step is done by assigning weights to each classification matrix obtained from the previous step. The assigning of the weights reflects our confidence in the segmentation decision of the corresponding level. The final classification step computes the confidence of each class and returns the class of the highest confidence, i.e., the winner class. For example consider that for a pixel I(x,y) the values of the classification matrices C_0, C_1, and C_2 were k_2, k_1, and k_1, respectively. And the weights assigned to them were (0.4), (0.35), and (0.25), respectively. Then the output of the reclassification step will be k_1. $I_0 I_1$Fig.1. Illustration of the use of Gaussian-window.

These weights, in our study, have been assigned such that they ensure the following points:

1.If $C_0(x,y)=C_1(x',y')=C_2(x'',y'')$ i.e. all the three pixels in $I(x,y)$, $I_1(x',y')$, and $I_2(x'',y'')$ belong to the same class, then $C(x,y)=C_0(x,y)$.

2.If $C_1(x',y')=C_2(x'',y'')$ $C_0(x,y)$ then $C(x,y)=C_1(x',y')$.

3.If $C_2(x'',y'')$ $C_1(x',y')$ then $C(x,y)=C_0(x,y)$. Where (x',y') is the parent of (x,y) and (x'',y'')is the grandparent of (x,y). Point two ensures that no pixels in the image I will be mistakenly assigned to some class k_1 while its parent and grandparent pixels belong to another class say k_2. Point three makes the classification decision is the decision of C_0, the classification matrix of the original image, if C_1 and C_2, the classification matrices of the parent and grandparent images, respectively, do not agree to the same class, or if C_0, C_1, and C_2 are all disagree. This is because we have assigned the leading weight to the classification matrix, C_0, of the original image. We did that because we think that the medical MR images contain many edges of high importance. For other types of images where the edges have less importance than the MRI then the greatest weight should be assigned to the classification matrix of the parent image or grandparent image. C.

3.3 THE GMEM ALGORITHM

The GMEM algorithm can be summarized in the following steps and as depicted in the flowchart shown in Fig. 2. 1-Start with an image I_o as input and generates its parent I_1 and grandparent I_2 using the Gaussian moving windows of sizes 3x3 and 5x5, respectively.

2-Apply the conventional EM algorithm for image segmentation on the images I_o, the parent I_1, and the grandparent I_2. The outputs of this step are the classification matrices C_0, C_1, and C_2, 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 I_0 after taking into account the spatial correlation between pixels.

4-Assign colors or labels to each class and generates the segmented image S.

Fig: 3 The GMEM flowcharts, the input is the image to be segmented, Io and the segmented images S.

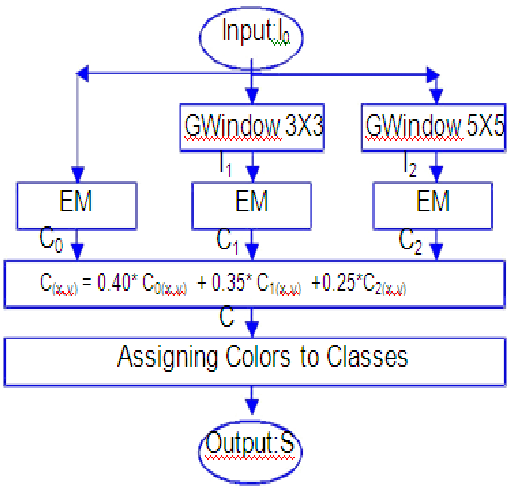
4. DRAWBACKS OF THE EM ALGORITHM

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 K_a, but if it has an intensity closer to the mean of another class, say K_b, the classifier would incorrectly classify this pixel to belong to class K_b.

This drawback is due to that the EM is based on 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 (Saeed, 1998).

5. RESULTS AND DISCUSSION.

Two types of data sets were used to evaluate the presented algorithms. The first type represents still images used to evaluate the resolution mosaic EM Algorithm (RM-EM). The second type of test data sets represents image sequences of various scenes for traffic monitoring. The first type includes three data sets: synthetic images, a magnetic resonance image (MRI), and simulated MR images. The first set of these data consists of two groups of synthetic images. They are created with certain specifications chosen to explore the advantages and disadvantages of the tested algorithms. The synthetic images allow quantitative comparisons between the differentAlgorithms, since the ground truth of the segmentation are known a priori. Each one of the synthetic images of both groups is of size 100×100 pixels and consists of four different classes. Each class is created by four Gaussian distributions with mean values 50, 100, 150, and 200. The layouts of the classes are chosen in a way that different types of edges and corners can appear which are interpreted as difficulties for the segmentation process. The images in the first group are created so that the classes are set in quadratic-chess form as shown in Fig..



In the second group the images are generated by two Gaussian distributions superimposed by two other Gaussian distributions as thin and thick lines as shown in Fig. .All the classes in an image are given the same standard deviation. This can be interpreted as the level of noise added to the image. Obviously, as the noise level increases, the difficulty of the segmentation process increases too. Therefore, three noise levels were used, ranging from low to very high. The standard deviations used are 10, 15 and 20. For each noise level an image in each group is created. The histograms are displayed in the same figures of the synthetic images. This helps to give an estimation of the increasing difficulties to the segmentation process as the noise level increases. The Gaussian distributions used to create the images of Figs. 4. It shows that with increasing noise level the overlapping areas between the distributions are also increased and the probability of error is increased too. The overlapped area between two classes is counted as Bayes error. A classifier, such as the minimum distance classifier, Cannot classify correctly the pixels lying in this area.

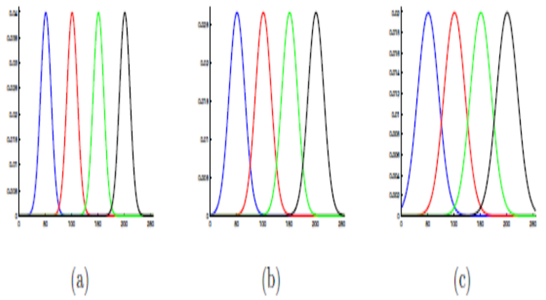


Figure:4. Gaussian distributions in a mixture model used for the synthetic Images. Mixture with (a) std = 10. (b) std = 15. (c) std = 20.

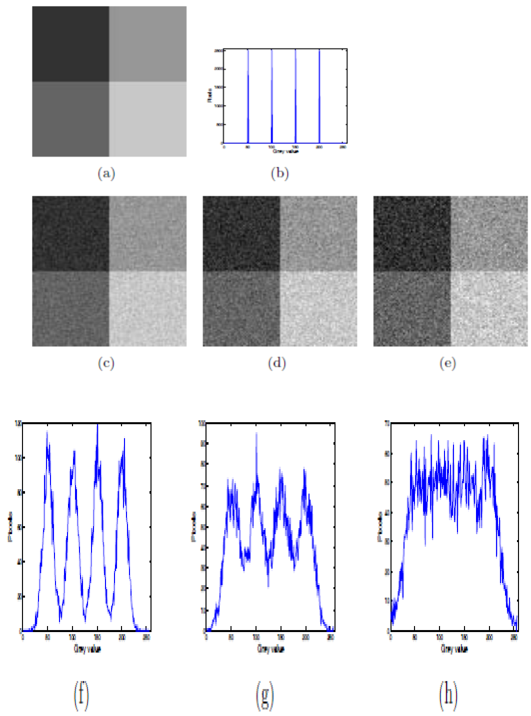


Figure 5: Synthetic quadratic images generated by four Gaussian distributions with mean values 50, 100, 150, and 200 and the associated histograms. (a) And (b) Without added noise. (c) and (f) With added noise std = 10. (d) and (g) std = 15. (e) and (h) std = 20.

The second data set is a real magnetic resonance image (MRI) of the human brain. Magnetic resonance images represent the intensity variation of radio waves generated by biological systems when exposed to radio frequency pulses. The image is representing a cross-sectional slice of the target. It can be divided into three regions other than the background. The first region represents the white matter (WM) of the brain tissue, the second the grey matter (GM), and the third region represents the cerebrospinal fluid (CSF) [AU96, UA96]. In MRI many fine features appear, such as edges or boundaries between different regions. Fig. 9.4 shows a real MR image of Size 206 × 167 and the three different tissues. The color of the CSF is the same color as the background. Therefore, they are segmented together in the same class.

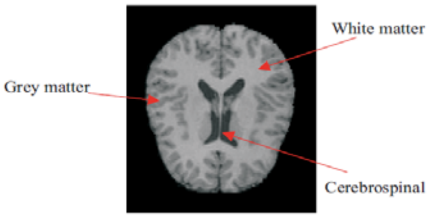


Figure 6: Real magnetic resonance image of the human brain.

The third data set consists of simulated MR images. The resulted segmented image by applying the EM algorithm on the real MRI is used as a labeled image to create the images belonging to this data set. Each pixel in a simulated MR image is generated by the Gaussian distribution of the class of the corresponding pixel in the label image. Again three values of standard deviations are used to create three test images, namely, 10, 15, and 20 to represent low, medium, and high noise level, respectively. Fig. shows the created images and their associated histograms. This data set is used because it is not possible to produce quantitative segmentation results
for the MRI because of the absence of the ground truth. Furthermore, its structure is very difficult to simulate by synthetic images.

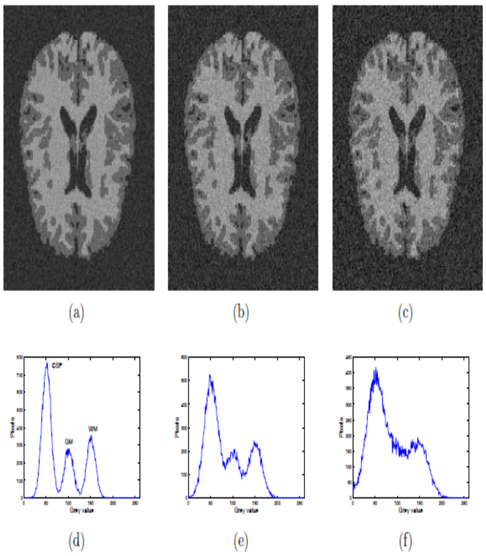


Figure 7: Simulated MRI generated by four Gaussian distributions with mean values 50, 100, 150, and 200 and the associated histograms. (a) and (d) std = 10. (b) And (e) std = 15. (c) and (f) std = 20.

6. CONCLUSION

The segmentation process is significantly speeded up. The number of iterations needed by the algorithm is reduced from 737 to 25 when a real MRI is segmented by the RM-EM instead of the EM. A new multiresolution algorithm for image segmentation has been proposed in this paper, namely, the Gaussian multiresolution EM algorithm (GMEM). The proposed algorithm is based on the conventional Expectation Maximization (EM) algorithm, and the multiresolution analysis of images. The EM has prevailed many other segmentation techniques because of its simplicity and performance. However, it is found to be very sensitive to noise level, where a drop of about 18% of the segmentation accuracy when noise increased from low to high levels, from variance = 100 to variance = 400. To overcome this drawback the GMEM algorithm uses the multiresolution analysis. The multiresolution analysis enables the algorithms to utilize the spatial correlation between neighboring pixels. The GMEM algorithm uses the Gaussian filter and the distinct block operation to generate low resolution images from the original image, where two images generated at two successive scales, the parent and the grandparent images. The proposed algorithm has been tested using both synthetic data and manually segmented magnetic resonance images (MRI). Moreover, performance analysis between this algorithm and the conventional EM algorithm has been presented. We found that the accuracy of the segmentation done by the proposed algorithm increased significantly over that of the conventional EM algorithm. In case of the synthetic data, about 15% increase in the segmentation overall accuracy (OA) is obtained for high noised images (variance = 400). In case of the real MR images with ground truth and added high Gaussian noise, an increase in the segmentation OA of about 9% is obtained. These results show that our new multiresolution algorithm provides superior segmentations over the one- scale image segmentation algorithms. The drawback found in the GMEM algorithm is that, when it is applied to pixels laying on the boundaries between classes or on edges, it generates many misclassified pixels, and this is because the parent and grandparent images contain only low frequencies and hence the edges are rarely appear in these images. Much of the error occurred because we used the classification of the parent and grandparent images to reclassify the pixels near the edges.

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