Proceedings of the 2nd Indian International Conference on Artificial Intelligence (IICAI-05).
Pune **INDIA** during **December 20-22 2005.**
Dspace@NITR http://dspace.nitrkl.ac.in/dspace

Brain MR Image Segmentation Using Tabu Search and Hidden Markov Random Field Model

P. K. Nanda, D. Patra and A. Pradhan

Image Processing and Computer Vision Laboratory
Department of Electrical Engineering
National Institute of Technology
Rourkela, Orissa, India, 769008
pknanda,dpatra@nitrkl.ac.in
achinta_p@rediffmail.com

Abstract. In this paper, we propose a hybrid Tabu Expectation Maximization (TEM) Algorithm for segmentation of Brain Magnetic Resonance (MR) images in both supervised and unsupervised framewrok. Gaussian Hidden Markov Random Field (GHMRF) is used to model the available degraded image. In supervised framework, the *apriori* image MRF model parameters as well as the GHMRF model parameters are assumed to be known. The class labels are estimated using the Maximum *a Posteriori* (MAP) estimation criterion. In unsupervised framework, the problem of model parameter estimation and label estimation is formulated in Expectation Maximization (EM) framework. The labels are estimated using the proposed Tabu Search algorithm while the model parameters are the maximum likelihood estimates. Our proposed algorithm yields results with arbitrary initial paramater set and thus overcomes the problem of proper choice of initial parameters. The results obtained are comparable with the results obtained by using the algorithm proposed by Zhang et.al. [15] , where the Iterated Conditional Mode (ICM) algorithm is used for computing the MAP estimates.

1 Introduction

Image segmentation is one of the early vision problem and has a wide application domain. The problem becomes more compounded while segmenting noisy scenes. For the last two decades, stochastic models, specifically, Markov Random Field (MRF) models have been used for image segmentation [1, 2]. MRF provides an unifying tool to provide a link between local and global characteristics of the image with the notion of neighbor structure. Geman and Geman[1] have proposed line fields with MRF models with a view to preserve the edges in noisy images. Often, the segmentation problem is formulated as pixel labelling problem and the pixel labels are estimated using the principle of Maximum *a Posteriori* Estimation (MAP) [1–3, 6]. Since computation of the MAP estimate is also a difficult problem, by and large, Simulated Annealing (SA) algorithm has been used to obtain the MAP estimates [3, 6]. The model based approaches for image segmentation can be viewed as either *supervised* or *unsupervised*. In the *supervised* framework, the associated model parameters are assumed to be known *a priori* [1–3, 6]. The problem is categorized as the *unsupervised* one when both the model parameters as well as the class labels are assumed to be unknown[2].

In the *supervised* framework, the associated model parameters are assumed to be known *a priori* [3, 6]. The problem is usually formulated as a pixel labelling problem using Bayesian approach. The MAP estimates of the pixel labels are obtained using SA algorithm [3]. In unsupervised framework, Besag [2] has proposed the coding scheme to estimate the model parameters while the image labels are estimated using the Iterated Conditional Mode (ICM) algorithm. The image labels and the model parameters are estimated in alternation. Eventually, this recursive algorithm converges to the optimal set of parameters and hence image segmentation. Deng et al. [4] has proposed an unsupervised scheme where they have estimated the model parameter and the class labels recursively. Recently, a tree-structured MRF based segmentation scheme is proposed in [5]. In [3], Nanda et.al. have proposed a Homotopy Continuation method for MRF model parameter estimation while the image labels are obtained using SA algorithm. The problem in unsupervised framework is a hard one because of the fact that both the parameters and the image labels are assumed to be unknown. In [2], even though ICM converges with in a few iterations, it has the inherent local convergence property. Simulated Annealing was found to be a potential alternative [3, 6] for quite sometime. The notion of Tabu Search can provide an alternate tool for such problems.

Tabu Search proposed by Glover [7–9] can be viewed as a strategy to solve combinatorial optimization problem and is an adaptive procedure which overcomes the limitations of local optimality. The notions of Tabu Search could be used to devise algorithms for image restoration [6] and segmentation [10]. In [6] and [10] Tabu Search has been used to obtain the MAP estimate of the image labels. In [6] a parallel Tabu Search algorithm is proposed to reduce the computational burden and the performance of the proposed Tabu Search algorithm is compared with that of the SA algorithm.

Segmentation of Brain Magnetic Resonance Images (MRI) has attracted attention of many researchers for the last decade [15, 11, 14]. Wells et al.[11] have proposed an adaptive brain MR image segmentation scheme in EM framework. EM algorithm proposed by Dempster [12] is a potential tool to handle incomplete data problem. Gu et al. [13] have proposed a EM algorithm based segmentation scheme while dealing with inhomogenous HMRF model. R. Guillemaud et.al.[14] have proposed a modified scheme in stochastic framework to estimate the bias field as well as pixel labels. Hidden Markov Model(HMM) have been extensively used for speech recognition[16]. Zhang et.al. [15] has proposed Hidden Markov Random Field (HMRF) model to model the observed degraded image in the context of segmentation. They have employed GHMRF model and has suggested a recursive scheme to estimate the GHMRF model parameters and the image labels simultaneously. They have formulated the problem in EM framework where

ICM has been used to obtain the MAP estimates. The algorithm proposed by Zhang et.al[15] greatly depends upon the choice of initial parameters.

In this article, we have addressed the problem of image segmentation in both *supervised* and *unsupervised* framework. The *a priori* class is modeled as a MRF model and the observed degraded image is modeled as HMRF model. Specifically, the observed image is modeled as Gaussian Hidden Markov Random Field (GHMRF). In supervised framework, the associated model parameters like mean (μ) and standard deviation (σ) of the Gaussian model are assumed to be known. The estimation of class labels are obtained by the Bayesian approach and the principle of Maximum a Posteriori(MAP) estimation. A Hybrid Tabu Search based algorithm is proposed to obtained the MAP estimates of the labels. Synthetic images of different classes are generated using Gibb's sampler[1]. The proposed algorithm could be successfully tested for synthetic as well as real Brain Magnetic Resonance Images (MRI).

In unsupervised framework, both the model parameters as well as the class labels are assumed to be unknown. Since this type of problem can be viewed as incomplete data problem, the problem is formulated in EM framework. In Expectation step, the MAP estimate of the image is obtained using an arbitrary parameter set. Earlier work by Zhang et.al.[15] have used ICM algorithm [2] to obtain the MAP estimate. Since ICM is a locally convergent algorithm, the algorithm needs a proper choice of initial parameters that are close to the optimal set. Our proposed algorithm does not need to have a proper initial choice of parameters. The algorithm starts from an arbitrary set of parameters. The MAP estimate of image labels is obtained using these arbitrary set and there after the expected value of the log likelihood function is computed. In the maximization step (M-step) of the EM algorithm, the GHMRF parameters like μ and σ are estimated. The parameter estimation and image estimation is carried out recursively until the parameters converge to the optimal set. The proposed Tabu-EM algorithm could be successfully tested for synthetic as well as real brain MR images. The results obtained by our proposed method were compared with that of the results obtained using Zhang's[15] approach and our results were visibly close to that of results obtained by using the method proposed by Zhang et. al.[15]. However, the potential feature of the proposed algorithm is that it starts from an arbitrary set of parameters. Simulation results presented demonstrates the efficacy of our proposed Tabu-EM algorithm.

2 Hidden Markov Random Field Model (HMRF)

Hidden Markov Models (HMM) have been applied to the problem of speech recognition [16]. HMMs are defined as stochastic processes generated by a Markov chain whose state sequence can not be observed directly, but only through a sequence of observations. Each observation is assumed to be a stochastic function of sate sequence. A special case of a HMM is considered, where the underlying stochastic process is a MRF instead of a Markov chain and therefore, not restricted to one dimension. This special case is referred to as Hidden Markov Random Field (HMRF) model [15].

Let the images are assumed to be defined on a discrete rectangular lattice S=N×N. Let X denote the random field associated with the labels of the original image. The label process X is assumed to be MRF with respect to a neighborhood system η and is described by its local characteristics.

$$\begin{aligned} P(X_{i,j} = x_{i,j} \mid X_{k,l} = x_{k,l}, k, l \in S, (k,l) \neq (i.j)) \\ = P(X_{i,j} = x_{i,j} \mid X_{k,l} = x_{k,l}, (k,l) \in \eta) \end{aligned}$$

Since X is a MRF, or equivalently Gibbs distributed, the joint distribution can be expressed as $P(X = x \mid \phi) = \frac{1}{Z} e^{-U(x,\phi)}$, where $Z = \sum_x e^{-U(x,\phi)}$ is the partition function, ϕ denote the clique parameter vector, *U(x,ϕ)* is the energy function and is of the form $U(X,\phi) = \sum_{c(i,j)\in c} V_c(x,\phi)$ is the clique potential. Y is the observed random field. For any potential realization x, the random variables Y_i are conditional independent

$$P(Y \mid X) = \prod_{i\in S} P(y_i \mid x_i) \tag{1}$$

The joint probability of (X,Y) can be expressed as

$$P(Y,X) = P(Y \mid X)P(X) = P(X) \prod_{i\in S} P(y_i \mid x_i)$$

According to the local characteristics of MRF, the joint probability distribution of pair (X_i, Y_i) given the neighborhood configuration of X_{η_i} is

$$P(y_i, x_i \mid x_{\eta_i}) = P(y_i \mid x_i) P(x_i \mid x_{\eta_i}) \tag{2}$$

Thus, the marginal probability distribution of Y_i dependent on θ and X_{η_i}

$$\begin{aligned} P(y_i \mid x_{\eta_i}, \theta) &= \sum_{l\in L} P(y_i, l \mid x_{\eta_i}, \theta) \\ &= \sum_{l\in L} P(y_i, l, \theta) P(l \mid x_{\eta_i}) \end{aligned} \tag{3}$$

where $\theta = \{\theta_l, l \in L\}$. (3) is the Hidden Markov Random Field model, L denotes the number of labels.
With Gaussian distribution, (3) can be expressed as

$$p(y_i \mid x_{\eta_i}, \theta) = \sum_{l\in l} g(y_i, \theta_l) P(l \mid x_{\eta_i}) \tag{4}$$

(4) is refereed to as the Gaussian Hidden Markov Random Field (GHMRF) model, where $g(y_i, \theta_l)$ is the Gaussian probability density function.

3 Image Segmentation

We have addressed the problem of Brain MR image segmentation in both supervised and unsupervised framework. Since in supervised framework the model parameters are assumed to be known, it is required to estimate the pixel labels using the associated model parameters. Let X be the random field associated with the noise free class label and x be the realization of the same. X is modeled as a MRF. Let Y denote the observed image random field and y be the realization of it. Y is modeled as Gauss Hidden Markov Random Field (GHMRF). Let θ be the associated model parameters.

3.1 Supervised Mode

In the pixel labeling problem, let x^* denote the true but unknown labeling configuration and $\hat{x}$ denote the estimate for x^*. x^* and $\hat{x}$ are realization of random field X, which is modeled as MRF. The observed image y is a realization of GHMRF. The problem is to recover x^* from the observed image y. The following optimality criterion is considered.

$$\hat{x} = {}^{arg\ max}_{\ \ x} \ P(X \mid Y, \theta) \tag{5}$$

where the model parameters for each class $\theta_l = [\mu_l, \sigma_l]$ are selected on an ad hoc basis. Since X is unknown, the posteriori probability distribution $P(X \mid Y, \theta)$ can not be evaluated. Hence, using Baye's rule, (5) can be expressed as

$$\hat{x} = {}^{arg\ max}_{\ \ x} \ \frac{P(Y \mid X, \theta) P(X)}{P(Y)} \tag{6}$$

Since Y is known. The denominator of (6) is a constant. Thus, (6) can be written as

$$\hat{x} = {}^{arg\ max}_{\ \ x} \ P(Y \mid X, \theta) P(X) \tag{7}$$

Since, X is a MRF, the prior probability distribution in (7) is given as $P(X) = \frac{1}{Z'} e^{-U(X)}$. It is also assumed that the pixel intensity y_i follows a Gaussian distribution with parameters $\theta_i = \{\mu_l, \theta_l\}$. Given the class label $x_i = l$,

$$P(y_i \mid x_i) = \frac{1}{\sqrt{2\pi\sigma_l^2}} exp\left(-\frac{(y_i - \mu_l)^2}{2\sigma_l^2}\right) \tag{8}$$

Using the assumption of conditional independence

$$P(Y \mid X) = \prod_{i \in S} P(y_i \mid x_i) = \prod_{i \in S} \left[\frac{1}{\sqrt{2\pi}} \left(-\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2} - log(\sigma_{x_i})\right)\right] \tag{9}$$

(9) can be expressed as

$$P(Y \mid X) = \frac{1}{Z'} exp(-U(Y \mid X))) \tag{10}$$

$$U(Y \mid X) = \sum_{i \in S} U(y_i \mid x_i) = \sum_{i \in S} \left[\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2} + log(\sigma_{x_i}) \right]$$

and $Z' = (2\pi)^{N/2}$. Using the above, (7) can be expressed as

$$\begin{aligned} \hat{x} &= ^{arg\ max}_{x} \left[\frac{1}{Z'} exp(-U(X)) \frac{1}{Z'} exp(-U(Y \mid X)) \right] \\ &= ^{arg\ max}_{x}\ exp\left[- \{ U(Y \mid X) + U(X) \} \right] \end{aligned} \tag{11}$$

(11) is equivalent to minimizing the following

$$\hat{x} = ^{arg\ min}_{x} \left[U(Y \mid X) + U(X) \right] \tag{12}$$

The MAP estimate in (12) is obtained by employing the proposed Hybrid Tabu search algorithm.

3.2 Tabu Search

Many optimization problems in practice require large space and more computational time in nonlinear framework. Extensive effort has been directed towards the design of good heuristics, in other words algorithm efficient with respect to computing time and storage space. Tabu Search (TS) is a general heuristic search procedure devised for finding a global minimum of a function which may be linear or nonlinear. It was developed by Glover [8] in 1986. This procedure has a flexible memory to keep the information about the past steps of the search and uses it to create and exploit the new solutions in the search space. Initially the Tabu Search algorithm starts from a random point or move X_{ini} and the next point obtained from the set of the feasible solutions by applying simple modification to X_{ini}. This modification is called a 'move' and the next point x_1 is the 'new point'. In order to avoid the algorithm's move to a new point in the search space which has been visited earlier, a Tabu list is introduced. Every successful move is stored in the Tabu list. The new move obtained will now be compared with all the earlier moves stored in the Tabu list and if the new move matches with any move in the Tabu list, it is discarded. The next point is again introduced and if the new point does not matches, then it is considered as a new point in the solution space. The use of Tabu list decreases the possibility of cycling, because it prevents returning, after a certain number of iterations, to a solution that has been visited recently. The Tabu list is updated with the new set of solutions. The best valued solution is selected as the next solution X_{next}. The moves stored in the Tabu list are the ones that were carried out most frequently and recently. This process also helps in overcoming the local minima problem.

3.3 Tabu Search Based Hybrid Algorithm

We have proposed the Tabu Search algorithm which mostly makes the Tabu array with recent moves of minimum energy but also moves with higher energy has been accepted with a probability. This strategy is our aspiration condition. The basic steps of the algorithm to obtain the MAP estimate is as follows.

Hybrid Tabu Algorithm

1. Initialize the initial temperature T_{in}.
2. The Initial Image of the algorithm is the degraded image.
3. A Tabu list, i.e. Tabu image set is created to store the recent moves, i.e. the image estimates of the algorithm. The set is of fixed length.
4. From the current move of the image, the next Tabu image is generated.
   i) Perturb $x_{ij}(t)$ with a zero mean Gaussian distribution with a suitable variance.
   ii) Evaluate the energy $U_p(x_{ij}(t+1))$ and $U_P(x_{ij}(t))$. If $\Delta f = (U_P(x_{ij}(t+1)) - U_P(x_{ij}(t))) < 0$, assign the modified value as the new value. If $\Delta f > 0$, accept the $x_{ij}(t+1)$ with a probability (if $exp(-\Delta f/T(x) > random(0,1))$.
   iii) Repeat step (ii) for all the pixels of the image.
5. Compute the power of the updated image $x(t+1)$ as $Px(t+1)$ and compare it with the powers of the Tabu list named as Tabu energy, if $Px(t+1) > P_{Tabu}$, accept $x(t+1)$ as Tabu image.
6. Aspiration condition: If $Px(t+1) > P_{Tabu}$, accept $x(t+1)$ as Tabu image with some probability.
7. Update the Tabu list.
8. Decrease the Temperature according to the logarithmic cooling schedule.
9. Repeat step 4-8 till the stopping criterion is met. In our simulation the stopping criterion is: the parameters do not change for three consecutive combined iterations.

3.4 Unsupervised Mode

In the unsupervised framework, we estimate the class labels and the model parameters alternately to obtain segmentation. The class labels are modeled as MRF model while the observed degraded image is modeld as GHMRF model. Since, the estimate of the optimal class labels is dependent on the estimate of optmial set of parameters, this can be viewed as an incomplete data problem. Hence, the MRF model parameters $\theta = \{\theta_l; l \in L\}$ need to be estimated. Specifically for Gaussian MRF model for the observed image y, the mean and standard deviation of each Gaussian class parameters $\theta_l = (\mu_l, \sigma_l)$ need to be estimated. In EM algorithm, the following criterion is adapted;

1. The missing part $\hat{x}$ is estimated with the current θ estimate and then $\hat{x}$ is used to form the complete data set $\{\hat{x}, y\}$.
2. θ is estimated by maximizing the expectation of complete data log likelihood $E[log\ P(X,Y \mid \theta)]$.

In this case, in E step, the MAP estimates of the class labels are obtained to form the complete data set. In the M step, the ML estimate of the parameter is computed using the class labels computed in E step.

E-step

MAP estimate of X is obtained by using the following optimality criterion.

$$\hat{X}^{(t)} =^{arg\ max}_{x} P(X \mid Y, \theta^{(t)})$$

and there after the expected value is computed as follows.

$$E[log\ P(x, y \mid \theta) \mid y, \theta^{(t)}]$$

M-step

ML estimate of parameters is obtained

$$\hat{\theta}^{(t+1)} =^{arg\ max}_{\theta} P(Y \mid \theta, X^{(t)})$$

The "E" and "M" steps are repeated till the parameters converge to the optimal set and hence segmentation.

Tabu Expectation Maximization Algorithm (TEM) The Maximum Likelihood estimate of the GHMRF model parameters are obtained by maximizing the likelihood function $P(Y \mid \theta, X(t))$. In the similar approach of Zhang [15], the update equation reduces to the following.

$$\mu_l^{(t+1)} = \frac{\sum_{i \in S} P^{(t)}(l \mid y_i) y_i}{\sum_{i \in S} P^{(t)}(l \mid y_i)} \tag{13}$$

$$\left(\sigma_l^{(t+1)}\right)^2 = \frac{\sum_{i \in S} P^{(t)}(l \mid y_i)(y_i - \mu_l)^2}{\sum_{i \in S} P^{(t)}(l \mid y_i)} \tag{14}$$

Tabu-HMRF-EM Algorithm

1. Initialize the class label to random values and take an arbitrary parameter set.
2. Compute the likelihood distribution $P^{(t)}(y_i \mid x_i)$ and estimate the class labels by MAP estimation.

$$\hat{x}^{(t)} =^{arg\ max}_{x} P(X \mid Y, \theta)$$

or in the other words

$$\hat{x}^{(t)} =^{arg\ min}_{x} [U(Y \mid X) + U(X)]$$

this is obtained by the proposed Tabu Search algorithm.

3. Compute the posterior distribution

$$P^{(t)}(l \mid y_i) = \frac{g^{(t)}(y_i \mid \theta_l) P^{(t)}(l \mid x_{\eta_i})}{P(y_i)}$$

4. Update the parameters

$$\mu_l^{(t+1)} = \frac{\sum_{i \in S} P^{(t)}(l \mid y_i) y_i}{\sum_{i \in S} P^{(t)}(l \mid y_i)}$$

$$\left(\sigma_l^{(t+1)}\right)^2 = \frac{\sum_{i \in S} P^{(t)}(l \mid y_i)(y_i - \mu_l)^2}{\sum_{i \in S} P^{(t)}(l \mid y_i)}$$

5. Step 2-4 are repeated until a fixed number of iterations.

4 Results and Discussions

We have validated the proposed algorithm in both supervised as well as unsupervised framework. Synthetic as well as real images are considered in both the above mentioned frameworks. Synthetic images consisting of different classes were generated using Gibb's sampler and GHMRF model. Although we have tested our algorithm for 3,4 and 5 classes for the sake of illustration,results for 3 class images are presented in this paper. Besides, results for two different real Brain MR images are presented to demonstrate the efficacy of the proposed schemes.

4.1 Supervised mode

In this mode we have presented results for a 3 class synthetic image and two real images as shown in Fig.1, Fig.2, Fig.3 respectively. The degraded images are obtained by adding white Gaussian noise to the original images. The observed degraded image is modeled as GHMRF while the class label is modeled as MRF. In supervised mode, the GHMRF parameters such as μ and σ for different classes are selected on an adhoc basis. The clique potential function for *apriori* MRF class model is given by

$$\begin{aligned} V_c(x) &= -\delta \quad if \quad |x_i - x_j| = 0 \\ &= \delta \quad if \quad |x_i - x_j| \neq 0 \end{aligned}$$

Where x_i and x_j are the pixel values of the i^{th} and j^{th} pixel respectively.

The parameters used for the synthetic image of figure 1 are: Initial temperature $T_{in} = 0.5$ and Tabu length $K = 10$. The original 3 class image is shown in Fig.1(a). The different noisy images are shown in Fig.1(b), (d), (f) and (h). Segmented images are shown in Fig.1(c), (e), (g) and (i) respectively. Eventhough, it is a 3 class image, initially five classes were assumed because of noisy conditions. Hence, the parameters used for different noisy conditions are presented in

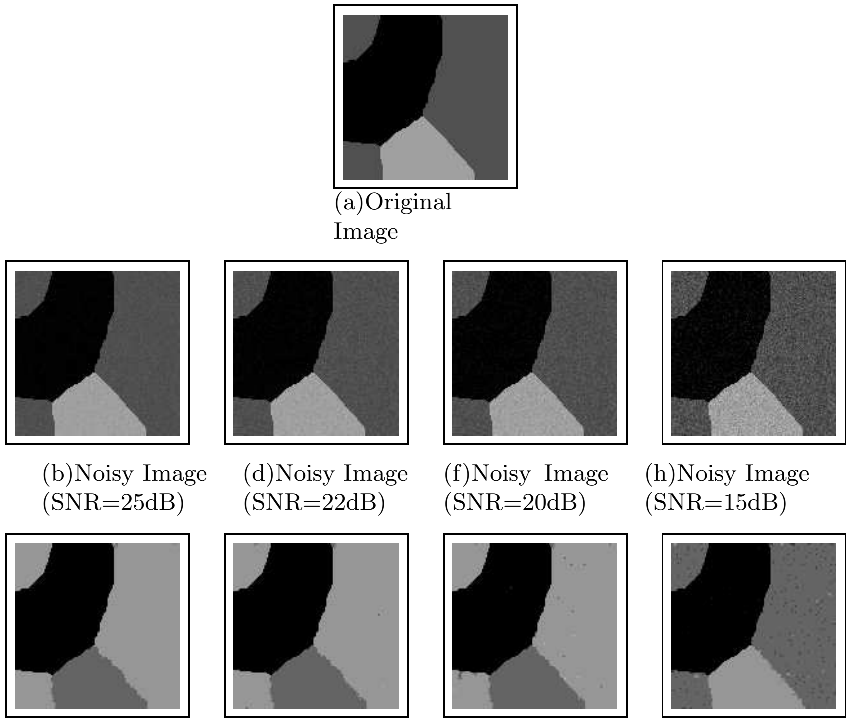
Table 1. As seen from Fig.1, proper segmentation could be achieved for noisy images upto SNR 22dB and for images of SNR 20 and 15dB, a few misclassified pixels are observed in Fig.1(g) and Fig.1(i). However, even in high noise conditions broadly three classes could be obtained. Thus the algorithm converged to 3 classes. The real images considered are shown in Fig.2 and Fig.3. Fig.2(a) shows the real brain MR image of size (74×100) and the noisy image of SNR 25dB is shown in Fig.2(b). The corresponding segmented image is shown in Fig.2(c). Because of noisy case , parameters for six classes as given in Table 2. are used to segment the noisy image. As observed from Fig.2(c) there are four broad classes in the segmented image and thus noisy image could be segmented. The parameters $T_{in}$and Tabu length K are same as that of the synthetic case. The 2nd real image considered is shown in Fig.3(a) and the noisy and segmented images are shown in Fig.3(b) and 3(c) respectively. The parameters used in this case are: $T_{in} = 0.1$ and Tabu length K=5. Because of noisy case, five initial classes are assumed and hence the parameters used for these five classes are shown in Table 3. However, as observed from Fig.3(c), the algorithm could segment into three broad classes and thus proper segmentation could be achieved.

Table 1. Parameters for Synthetic 3-class Image of size (128x128) corresponding to Fig.1 in supervised mode

$Class \rightarrow$	1	2	3	4	5
μ_{25dB}	0.027	0.991	1.995	2.0	1.0
σ_{25dB}	0.104	0.109	0.981	0.4	0.02
μ_{22dB}	0.027	0.991	1.995	2.0	1.0
σ_{22dB}	0.104	0.103	0.98	0.4	0.02
μ_{20dB}	0.027	0.991	1.995	2.0	1.0
σ_{20dB}	0.104	0.109	0.98	0.4	0.02
μ_{15dB}	0.051	0.991	1.996	2.419	1.0
σ_{15dB}	0.207	0.19	0.5	0.7	0.12
δ			1		

Table 2. Parameters for Brain MR Image of size (74x100) having SNR=25dB corresponding to Fig.2 in supervised mode

Class	1	2	3	4	5	6
μ	0.052	2.6248	1.5974	3.265	2.0	1.0
σ	0.079	4.86	0.562	0.408	0.257	0.2
δ			0.28			

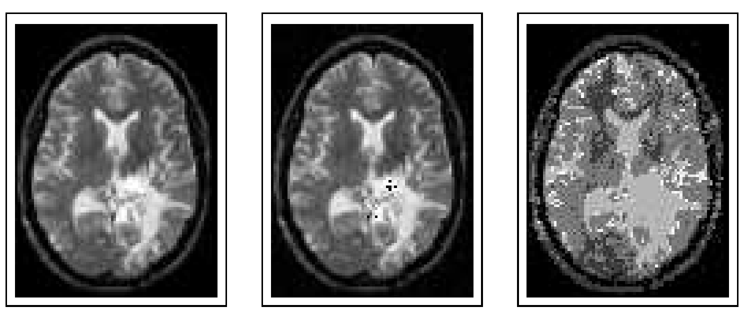


(a)Original Image

(b)Noisy Image (SNR=25dB) (d)Noisy Image (SNR=22dB) (f)Noisy Image (SNR=20dB) (h)Noisy Image (SNR=15dB)

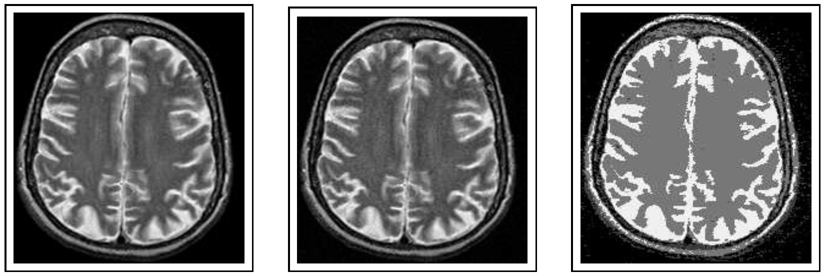
(c)Segmented Image (SNR=25dB) (e)Segmented Image (SNR=22dB) (g)Segmented Image (SNR=20dB) (i)Segmented Image (SNR=15dB)

Fig.1: Segmented images for different noisy synthetic three class images of size (128x128) in supervised mode.



(a)Original Image (b)Noisy Image (c)Segmented Image

Fig.2: Supervised Image Segmentation of Real Brain MR Image of Size (74x100) having SNR=25dB.



(a)Original Image (b)Noisy Image (c)Segmented Image

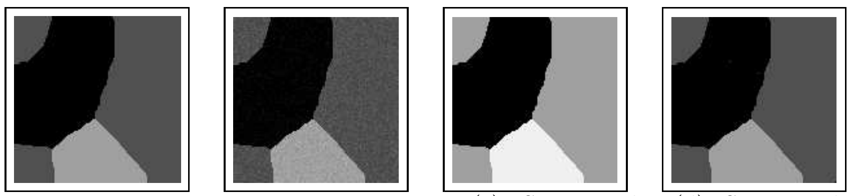
Fig.3: Supervised Image Segmentation of Real Brain MR Image of Size (189x205) having SNR=25dB.

Table 3. Parameters for Brain MR Image of size (189x205) having SNR=25dB in supervised mode

Class	1	2	3	4	5
μ	0.1	0.5	1.5	1.5	2.0
σ	0.5	0.5	0.5	1.5	1.5
δ	0.1				

4.2 Unsupervised mode

The synthetic 3 class image considered for our simulation is shown in Fig.4(a). The corresponding noisy image of SNR 20dB is shown in Fig.4(b). We have assumed 5 initial classes and hence the initial set of parameters are presented in Table 4. The algorithm converged to the optimal set as given in Table 4. The segmented result obtained using these parameters is shown in Fig.4(c). The algorithm starts from an arbitrary set. It is evident from Table 4 that the algorithm starts from $\mu = 0.3$ and $\sigma = 0.1$ for the first class and converges to $\mu = 0.031$ and $\sigma = 0.046$ after around 18 combined iterations. The parameters used in TEM algorithm are $T_{in} = 0.1$ and Tabu length K=5. Our result is also compared with that of the algorithm proposed by Zhang et. al.[15] where ICM algorithm is used. The result obtained by Zhang's[15] approach is presented in Fig.4(d). By comparing Fig.4(c) and Fig.4(d), it is clear that the segmented image of Fig.4(c) is visually same as that of Fig.4(d). It is to be noted that the result shown in Fig.4(c) is obtained from an arbitrary initial parameter set where as the result presented in Fig.4(d) is obtained from a proper choice of initial parameter set. Zhang et. al.[15] has outlined the histogram method to obtain a initial parameter set. In order to validate the proposed algorithm the algorithm was run with different initial parameters sets. For the first class, the different starting conditions of μ and σ with the convergence conditions are shown in Fig.5(a) and Fig.5(b). It is observed from Fig.5(a) and Fig.5(b) that the parameters μ converged to a value of 0.031 despite starting from different initial values. Similar phenomenon is also observed for σ as demonstrated in Fig.5(b). This demonstrates that the algorithm does not require to have a proper choice of initial parameters. The algorithm was also tested for real Brain MR images as shown in Fig.6 and Fig.8. Fig.6(a) shows the original image of size (189×205) and the corresponding noisy image of SNR 25dB is shown in Fig.6(b). The parameters used in the algorithm are $T_{in} = 0.1$ and Tabu length K=5. The noisy image was input to the algorithm and five different classes were assumed initially. The initial values of μ and σ for five different classes are given in Table 5. However, the algorithm converged to four different classes as seen from Fig.6(c). It is also observed from Fig.6(c) that proper segmentation could be achieved even starting from different initial conditions. The results obtained using Zhang's approach is shown in Fig.6(d). Results obtained by our proposed algorithm is very much comparable with Zhang's approach. The convergence of μ and σ for different initial conditions are shown in Fig.7(a) and (b). It is observed that even though the algorithm started from different initial conditions, the parameters μ and σ converged to a optimal set.



(a) Original Image

(b) Noisy Image (SNR=20dB)

(c) Segmented Image (Using TEM algo.)

(d) Segmented Image (Using Zhang's algo.)

Fig.4: Unsupervised Image Segmentation of 3 class Synthetic Image of Size (128x128)

Table 4. Parameters for 3 class Synthetic Image of size (128x128) having SNR=20dB corresponding to Fig.4 in unsupervised mode.

Class		1	2	3	4	5
Initial	μ	0.3	0.2	0.8	0.8	0.2
	σ	0.1	0.2	0.1	0.4	0.2
Final	μ	0.031	0.012	0.992	1.99	0.0
	σ	0.046	0.0012	0.104	0.099	0.0001
δ	1.2					

The algorithm was also tested for another real Brain MR image as shown in Fig.8(a). We have validated our result with four different noisy images of SNR 25,22,20 and 18dB, but for the sake of illustration, we present the case of a noisy image of SNR 22dB as shown in Fig.8. The segmented results shown in Fig.8(c),(d),(e) and (f) correspond to 4 different initial parameter sets. The initial

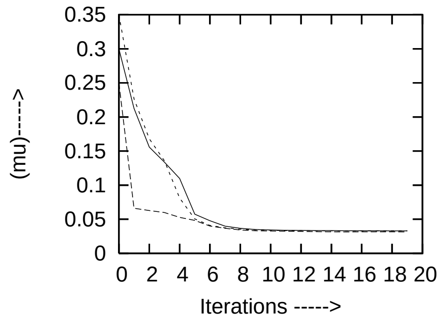


Fig.5(a) μ for the 3-class of synthetic image of size (128x128) having SNR 20dB for different initial conditions corresponding to Fig.4.

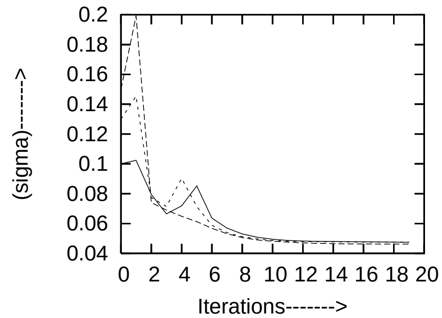
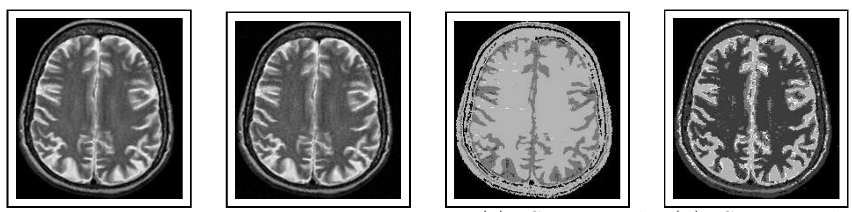


Fig.5(b) $\sigma$for the 3-class of synthetic image of size (128x128) having SNR 20dB for different initial conditions corresponding to Fig.4.



(a) Original Image

(b) Noisy Image (SNR=25dB)

(c) Segmented Image (Using TEM algo.)

(d) Segmented Image (Using Zhang's algo.)

Fig.6: Unsupervised Image Segmentation of brain MRI image of size (189x205)

and final parameter sets for these four different conditions are given in Table 6. The convergence of the μ and σ starting from four different initial conditions are shown in Fig.9(a) and (b) respectively. It is observed from Fig.9(a) that although μ starts from four diffrent values, it converges to a optimal set. The parameter σ could be selected with wide differernce for a given class (first class) and, as clearly seen, all the four converges to almost values that are very close to each other. This demonstrates the fact that the proposed algorithm does not depend upon the proper choice of parameters. It is clear from the results presented in Fig.8 that proper segmentation could be achieved for four different starting conditions. However, in our formulation, we assume to have *a priori* knowledge of the parameter "δ". Thus, proper segmentation could be achieved for synthetic as well as real images.

5 Conclusion

In this paper we have proposed supervised and unsupervised image segmentation schemes. The problem is formulated as a pixel labelling problem. In both the cases, the class labels are modeled as MRF and the observed image as GHMRF

Table 5. Parameters for Real Brain MR Image of size (189x205) having SNR=25dB for different classes corresponding to Fig.5 for different initial conditions.

$Class \rightarrow$	1	2	3	4	5
μ_{i1}	0.5	4.	3.	2.	2.
σ_{i1}	0.5	0.5	0.5	2.	2.
μ_{f1}	0.054	3.68	3.11	1.46	1.38
σ_{f1}	0.024	0.07	0.4	0.19	0.074
μ_{i2}	0.45	4.3	3.2	1.9	2.1
σ_{i2}	0.45	0.4	0.45	1.9	2.1
μ_{f2}	0.05	3.63	2.61	1.45	1.37
σ_{f2}	0.02	0.09	0.47	0.17	0.07
μ_{i3}	0.51	3.8	3.1	1.8	2.2
σ_{i3}	0.52	0.42	0.43	2.2	1.8
μ_{f3}	0.053	3.68	3.21	1.47	1.45
σ_{f3}	0.023	0.067	0.34	0.2	0.07
δ	0.5				

model. The model parameters were selected on an ad hoc basis in supervised framework. In supervised scheme, the MAP estimates are obtained using the proposed hybrid Tabu algorithm. The scheme could yeild successful results for real as well as synthetic images. Our unsupervised scheme is based on EM framework. The proposed TEM unsupervised scheme has the attribute to converge to the optimal set of parameters starting from an arbitrary set. Thus, this does not require to have proper choice of initial parameters. This does not ofcourse imply the parameters can be selected at random. Neverthless, the parameters can be selected from an arbitrary set. The algorithm could be successfully tested for synthetic as well as real images. Our results were compared with the results obtained using Zhang's approach and it was observed that our results are visually close to Zhang's method. It is to be noted that our algorithm starts from an arbitrary set while Zhang's approach needs proper choice of initial parameters. In both the schemes, the *a priori* model parameter δ is selected on an ad hoc basis. Hence, the proposed algorithm which has a globally convergent attribute may be preferred to the algorithm that requires a proper choice of initial parameters. Currently attempts are made to estimate the model parameter δ together with other parameters.

6 Acknowledgement

This work is supported by the project on "Real-time Signal and Image Processing Using Soft Computing Approach", funded by MHRD, Govt. of India.

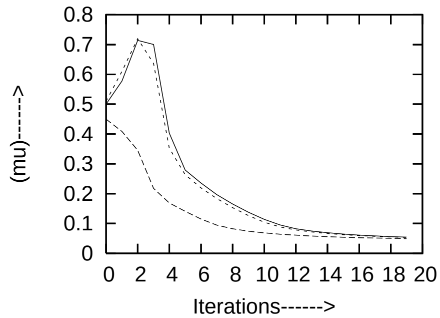


Fig.7(a) μ for the first class of Real brain MR image of size (189x205) having SNR 25dB for different initial conditions corresponding to Fig.5.

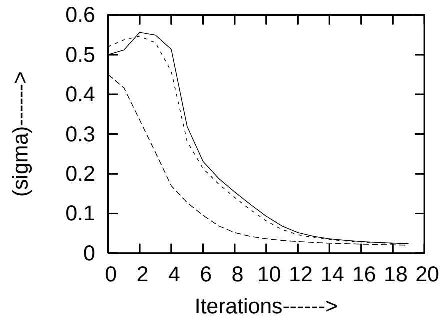
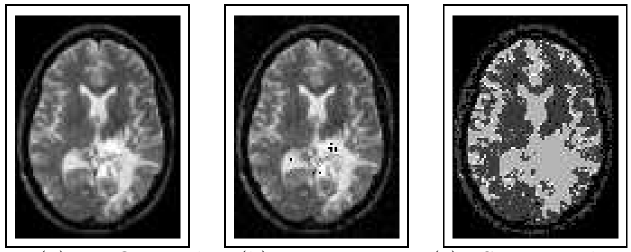


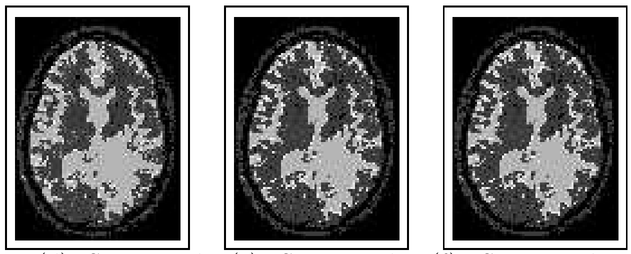
Fig.7(b) $\sigma$for the first class of Real brain MR Image of size (189x205) having SNR 25dB for different initial conditions corresponding to Fig.5.

References

1. Geman, S. and Geman, D.: Stochastic relaxation, Gibbs distribution and Bayesian restoration of images. IEEE Trans. On Pattern Analysis and Machine Intell. **6(6)** (1984) 721-741.
2. Besag, J.: On the statistical analysis of dirty pictures. J. Roy Sta. Soc. Series B. **48(3)** (1986) 259-302.
3. Nanda, P. K., Ponacha, P. G. and Desai, U. B. : A Supervised Image Segmentation scheme using MRF Model and Homotopy Continuation Method. In: Proc. of Indian conference on computer Vision, Graphics and Image Processing. Dec. 21-23 (1998) 15-20.
4. Deng, H. and Clausi, D. A. : Unsupervised image segmentation using a simple MRF model with a new implementation scheme. Pattern Recognition **(37)** (2004) 2323-2335.
5. D'Elia, C., Poggi, G, and Scarpa, G. : A Tree-Structured Markov Random Field Model for Baysian Image Segmentation. IEEE Trans. on Image Processing **12(10)** (2003) 1259-1273.
6. Nanda, P. K. and Patra, Dipti.: Parallel Tabu Search Hybrid Algorithm for Image Restoration. In: Proc. Of International Conference on Communication devices and Intelligent Systems. CODIS-2004, Kolkata. 8-10 Jan. (2004) 532-535,
7. Glover, F. and Laguna, M.: Tabu Search. Kluwer Academic Publishers. Boston. (1997)
8. Glover, F.: Tabu Search part I. ORSA Journal on Computing. **1(3)**. (1989) 190-206.
9. Glover, F.: Tabu Search part II. ORSA Journal on Computing. **2(1)** (1990) 4-32.
10. Jiang, T. and Yang, F.: An Evolutionary Tabu Search cell Image Segmentation. IEEE Trans. on System Man and Cybernetics. Part B. **32(5)** (2002) 675-678.
11. Wells, W. W., Grimson, W. E. L, Kikinis, K. and Jolesz, F. A.: Adaptive segmentation of MRI data. IEEE Trans. on Medical Imaging. **15(4)** (1996) 429-442.
12. Dempster, A. P., Laird, N. M. and Bubin, D. B.: Maximum Likelihood from Incomplete data via EM algorithm. J. Royal Statistical Society. ser. B. **39(1)** (1977) 1-38.



(a) Original Image (b) Noisy Image (c) Segmented Image



(d) Segmented Image (e) Segmented Image (f) Segmented Image

Fig.8: Unsupervised Image Segmentation of Real Brain MR Image of Size (74x100) having SNR=22dB. Fig.7 (c), (d), (e) and (f) show the results coresponding to four diffrent initial conditions.

Table 6. Parameters for Real Brain MR Image of size (74x100) having SNR=22dB for different initial conditions corresponding to Fig.7.

$Class \rightarrow$	1	2	3	4	5	6
μ_{i1}	0.54	1.2	1.6	2.5	2.1	1.0
σ_{i1}	0.57	0.18	0.01	0.13	0.03	0.02
μ_{f1}	0.032	1.368	1.593	2.430	2.108	1.00
σ_{f1}	0.049	0.128	0.0126	0.1155	0.026	0.0288
μ_{i2}	0.5	1.3	1.63	2.54	2.1	1.0
σ_{i2}	0.55	0.16	0.03	0.13	0.04	0.03
μ_{f2}	0.0321	1.368	1.593	2.43	2.1	1.0
σ_{f2}	0.049	0.128	0.012	0.1155	0.026	0.0288
μ_{i3}	0.52	1.2	1.53	2.6	2.3	1.1
σ_{i3}	0.63	0.18	0.03	0.15	0.03	0.01
μ_{f3}	0.031	1.335	1.522	2.555	2.288	1.095
σ_{f3}	0.048	0.1188	0.016	0.226	0.0158	0.011
μ_{i4}	0.61	1.25	1.6	2.45	2.2	1
σ_{i4}	0.6	0.18	0.01	0.13	0.03	0.03
μ_{f4}	0.03	1.42	1.6	2.47	1.96	1.02
σ_{f4}	0.0478	0.138	0.001	0.099	0.035	0.016
δ	0.28					

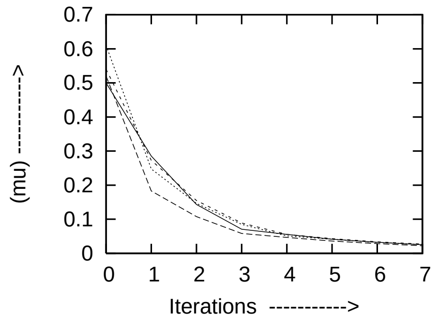


Fig.9(a) μ for Real brain MR Image of size (74x100) having SNR 22dB for different initial conditions corresponding to Fig.8.

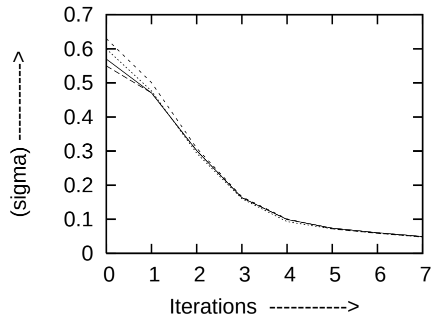


Fig.9(b) σ for Real brain MR Image of size (74x100) having SNR 22dB for different initial conditions corresponding to Fig.8.

13. Gu. D. B. and Sun, J. X. : EM image segmentation algorithm based on an inhomogenous hidden MRF model. IEE Proc. Vision Image Signal Processing. **152(2)** (2005) 184-190.
14. Guillemaud, R. and Brady, M.: Estimating the Bias Field of MR Images. IEEE Trans. on Medical Imaging. **16(3)** (1997) 238-251.
15. Zhang, Y., Brady, M. and Smith, S.: Segmentation of brain MR images through a Hidden Markov Random Field Model and the Expectation Maximization Algorithm. IEEE Trans. on Medical Imaging. **20(1)** (2001) 45-57.
16. Rabiner. L. R.: A tutorial on Hidden Markov Models and selected applications in speech recognition. Proc. IEEE. **77** (Feb. 1989) 257-286.