Fast Unsupervised Bayesian Image Segmentation with Adaptive Spatial Regularization

Manisha*, Gitanjali Pandove**
*M.Tech Scholar, ECE Department, D.C.R.U.S.T, Murthal
** Associate Professor, ECE Department, D.C.R.U.S.T, Murthal

Abstract

Image segmentation is a process of dividing the image in to some distinct regions. These region shave specially coherent in nature and have similar attributes. This technique is widely used for image analyses and to interpret the desired feature. In this present paper we will study about the hidden Markov random fields and find its expectation maximization algorithm. The main idea behind developing HMRF is to adjoin the “data faithfulness” and “model smoothness”, that show very similar nature with the active contours, GVF, graph cuts, and random walks. Here we also uses the HMRF-EM along with the Gaussian mixture models, and then we use it on color image segmentation process. These algorithms are implemented in MATLAB. In color image segmentation experiments, we observe that the result obtain from HMRF segmentation are much smoother then the direct k-means clustering. The segmented object is much closer to the original shape than clustering.The segmentation time for Bacteria 1, Bacteria 2, SAR & brain images are 0.35, 0.43, 0.12 and 0.12 respectively. The accuracy for Bacteria, Bacteria 2, SAR & brain images are 97.70 %, 98.06%, 98.89% and 97.35 % respectively.

Key Words:Image segmentation, Bayesian methods, spatial mixture models, Potts Markov random field, convex optimization.

I. Introduction

If we study about the image processing system, the resulted image may contain some irregularities or defects that may affect our process. Furthermore these kind of defects can be adjusted by various kind of techniques like increase the number of picture from the same scene which decrease the effect of defect and by using a higher quality instruments, but such methods which are based on the external hardware are consume more time and they increase the cost too [1]. So to avoid such effect of external hardware we often used computer programs which consume very less time and reduce the cost. For example to remove the noise defect we can use smooth filter which effectively reduce the noise content and filter the image or to change the contrast level in a low contrast image we can use image histogram by which level can be scaled. Such correction of various defect in image is called image pre processing [2].

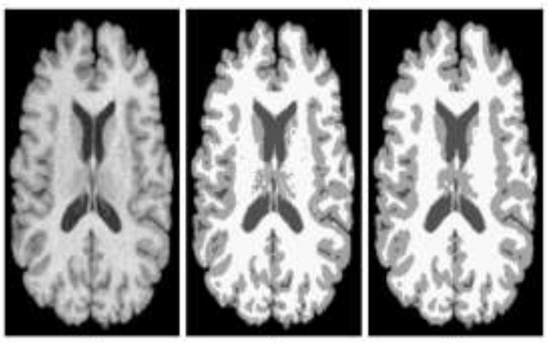
After removing the defects the process of image segmentation occurs. For example segmentation of food image which means to distinguish automatically the food products from an image is obviously carried out after image acquisition because this process of segmentation is completely carried out by the computer programs and there is no need of human intervention between the process the computer itself recognize the food items. If we defining the image segmentation in simple words, the image segmentation process divide the image in to several well defined regions. All these regions have similar pixels characteristics and attributes. As image segmentation is a important task because all the object classification and object measurement i.e. interpretation task is completely based on the results of segmentation process. A high quality of effort are being used to obtain an optimal segmentation techniques but till now there is no such technique are available. [3].

But still there are various kind of segmentation techniques are available which gives effective results. In food industry four kind of segmentation techniques are most used which are on the basis of region, threshold base and on the basis of classification. But these techniques cannot provide a high accuracy result if it used for a wide range of food products. Some further methods which are an combined effect of above techniques are also being developed that compromise on accuracy of results [4].

The rest of research paper is design as follows. The Markov Random Field Model in Section II. Section III describes problem formulation. Performance parameter describe in section IV. Finally, Section V describes the conclusion of paper.

II. Markov random field models

The markov random field is not a segmentation technique but this is the segmentation method which we used under the color segmentation process of images. In MRFs model we have some spatial relation among neighbor or adjustment pixels. Thus such kinds of relation among pixels are used to model the various image properties. We use this technique in medical imaging to ensure that the pixels are belongs to the same class as to their neighbor pixel class.
Sometime we also use the MRFs model in the clustering segmentation algorithms. Figure 3c, depicts the robust nature of noise in the segmented outcomes.



(a) (b) (c)

Figure 1 Segmentation of a Magnetic Resonance brain image.

III. Proposed Algorithm

Now days the most important application of Markov random fields are in computer vision problems, like automatic image segmentation, surface reconstruction, and depth inference. Much of its success attributes to the efficient algorithms, such as Iterated Conditional Modes, and its consideration of both "data faithfulness" and "model smoothness".

The HMRF-EM framework was firstly used to propose the segmentation of brain MRI images. For simplicity, we first assume that the images are in two dimensional array, and the intensity distribution in each segmented region follow the Gaussian distribution. Given an image Y = (y_1; : : : ; y_N) here N shows the number of pixel and each yi shows the gray-level intensity of a pixel, we want to infer a configuration of labels **X** = (x_1; : : : ; x_N) where xi 2 L and L is the set of all possible labels. In a binary segmentation problem, L = f0; 1g. According to the MAP criterion, we seek the labeling X Which satisfies:

$$X^* = \underset{X}{argmax} \{P(Y \mid X,\theta)P(X)\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The prior probability P(X) is a Gibbs distribution, and the joint likelihood probability is

$$P(Y \mid X,\theta) = \prod_i P(y_i \mid X,\theta)\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$= \prod_i P(y_i|x_i\theta_{xi}), \ldots\ldots\ldots\ldots\ldots(3)$$

Where $P(y_i \mid x_i,\theta_{xi})$ is a Gaussian distribution with parameters θxi = (μ_{xi}, σ_{xi}), In MRF problems, people usually learn the parameter set θ = {$\theta_l \mid$ l ∈ L } from the training data. For example, in image segmentation problems, prior knowledge of the intensity distributions of the foreground and the background might be consistent within a dataset, especially domain specific dataset. Thus, we can learn the parameters from some images that are manually labeled, and use these parameters to run the MRF to segment the other images. The major difference between MRF and HMRF is that, in HMRF, the parameter set θ is learned in an unsupervised manner. In a HMRF image segmentation problem, there is no training stage, and we assume no prior knowledge is known about the foreground/background intensity distribution. Thus, a natural proposal for solving a HMRF problem is to use the EM algorithm, where parameter set θ and label configurations X are learned alternatively.

EM Algorithm for Parameters

We still use the 2D gray-level and Gaussian distribution assumption. We use the EM algorithm to estimate the parameter set ɵ = $\{\theta_l \mid l \in L)$We describe the EM algorithm by the following:

1. Start: Assume we have an initialize parameters set$ɵ^{(0)}$

2. Next step: At the ith iteration, we have $ɵ^{(t)}$ and we calculate the exception conditionally

   $Q(ɵ \mid ɵ^{(t)}) = E[\text{ in } P(X,Y \mid ɵ) \mid Y, ɵ^{(t)}] = \sum_{x \in X} P(X \mid Y, ɵ^{(t)}) \text{ in } P(X,Y \mid ɵ)$

where is the set of all possible configurations of labels.

3. M-step: Now maximize $q(ɵ \mid ɵ^{(t)})$ to obtain the next estimate:

$$ɵ^{(t+1)} = \underset{ɵ}{argmax}\, Q(ɵ \mid ɵ^{(t)}) \text{ ……………………(4)}$$

Then let ɵ (t+1) → $ɵ^{(t)}$ and repeat from the E-step.

Let G(z; θ_l) denote a Gaussian distribution function with parameters $\theta l = (\mu l; \sigma l)$:

$$G(z;\theta_l) = \frac{1}{\sqrt{2\pi\sigma_l^2}} \exp\left(-\frac{(z-\mu_l)^2}{2\sigma_l^2}\right) \text{ …………………..(5)}$$

We assume that the prior probability can be written as

$$P(X) = \frac{1}{Z} \exp(-U(X)) \text{ …………………….(6)}$$

Where U(x) is the prior energy function. We also assume that

$$P(Y \mid X, ɵ) = \prod_i P(y_i \mid x_i, \theta_{xi})$$

$$= \prod_i G(y_i;\theta_{xi}) = \frac{1}{Z'} \exp(-U(Y \mid X))$$

With these assumptions, the HMRF-EM algorithm is given below:

1. Start with initial parameter set $ɵ^{(o)}$

2. Calculate the likelihood distribution$P^{(t)}(y_i \mid x_i, \theta_{xi})$.

3. Using current parameter set ɵ(t) to estimate the labels by MAP estimation:

$$X^{(T)} = \underset{X \in x}{argmax} \{ P(Y \mid X, ɵ^{(t)}) P(X) \} = \underset{x \in x}{argmin} \{ U(Y \mid X, ɵ^{(t)}) + U(X) \} \text{……………(8)}$$

4. Calculate the posterior distribution for all l ∈ L and all pixels y_i using the Bayesian rule:$P^{(t)}(l \mid y_i) = \frac{G(y_i;\theta_l) P(l \mid x_{N_i}^{(t)})}{P^{(t)}(y_i)}$ ………………………(9)

Where $x_{N_i}^{(t)}$ is the neighborhood configuration of $x_i^{(t)}$, and$P^{(t)}(y_i) = (y_i) = \sum_{l \epsilon L} G(y_i; \theta_l) P) l \mid x_{N_t}^{(t)}),$

Note here we have $P(l \mid x_{N_i}^{(t)}) = \frac{1}{Z} \exp(-\sum_{j \epsilon N,} V_c(l, x_j^{(t)})$ ……………(10)

5. Use P(t)(ljyi) to update the parameters:

$$\mu_l{}^{(t+1)} = \frac{\sum_i P^{(t)}(l \mid y_i) y_i}{\sum_i P^{(t)}(l \mid y_i)}$$

$$(\sigma_l{}^{(t+1)})^2 = \frac{\sum_i P^{(t)}(l \mid y_i)(y_i - \mu_l^{(t+1)})^2}{\sum_i P(t)(l \mid y_i)} \text{ ………….. (11)}$$

IV. Result Analysis

In the proposed work, we have taken lungs , bacteria , brain and SAR images for segmentation.

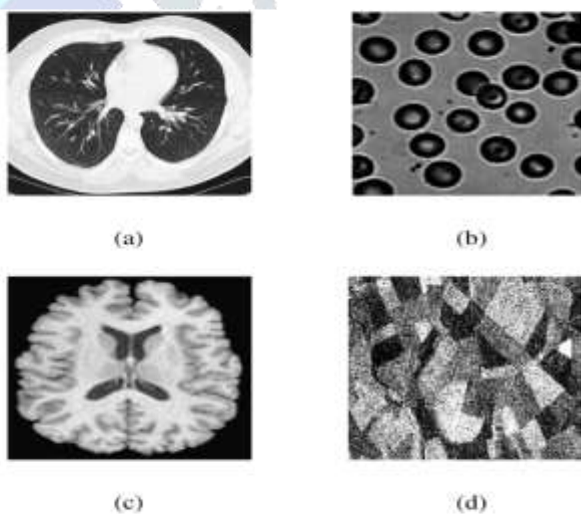


Fig.2. Lungs, Bacteria, Brain and SAR images before segmentation

Fig.2. ShowsLungs, Bacteria, Brain and SAR images before segmentation. These are the original images used as data base.

Fig 3 Original Lung Image

The original Lung Image is shown in fig 3.

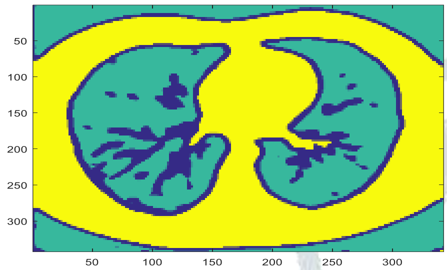


Fig.4.Lung image after proposed algorithm

The EM algorithm is applied to different Images. The lung image is shown in the fig 4.

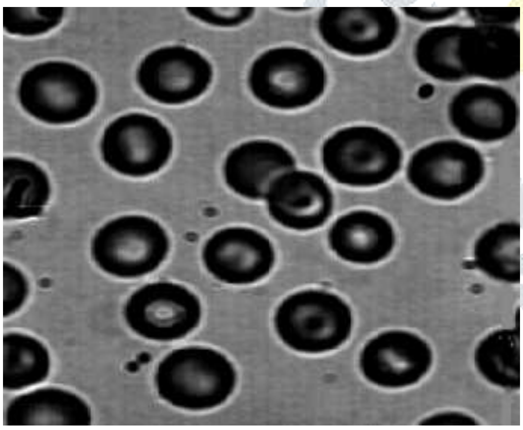


Fig 5 Original Bacteria Image

The original Lung Image is shown in fig 5.

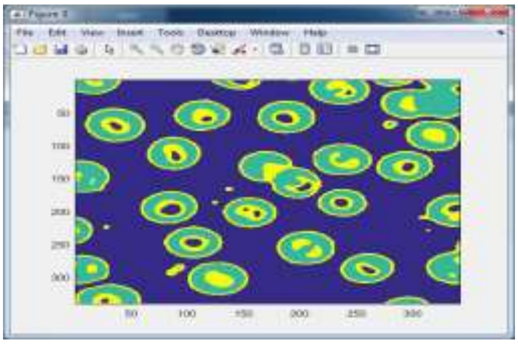


Fig. 6. Bacteria image after proposed algorithm

The proposed algorithm is applied to bacteria images also. Bacteria Image is uploaded in this algorithm.

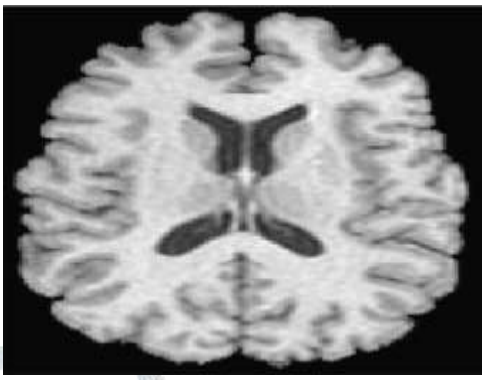


Fig 7 Original Brain Image

The original Brain Image is shown in fig 5.

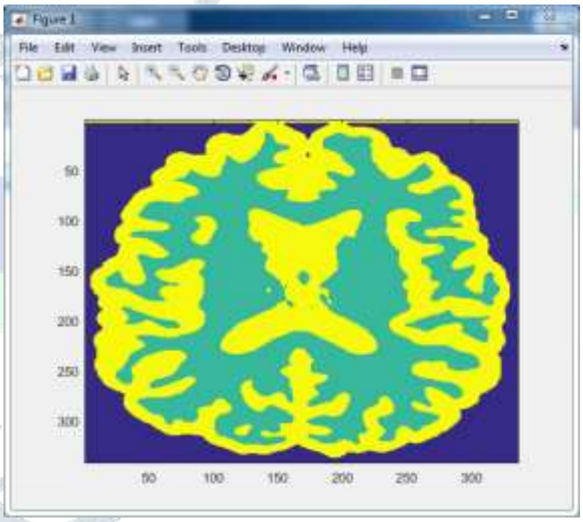


Fig.8. Brain image after proposed algorithm

Brain image after proposed algorithm is shown in Fig 8

Fig 9 Original SAR Image

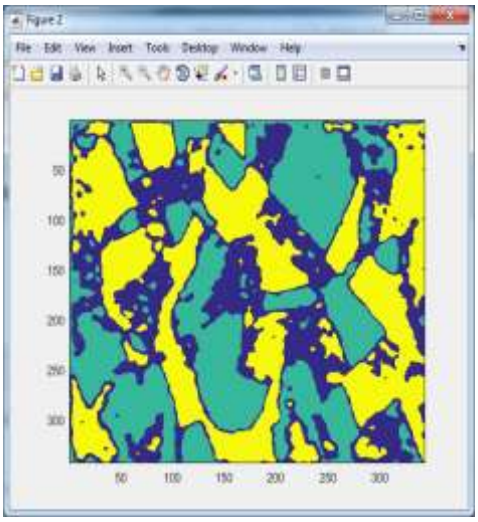


Fig 10 SAR image after proposed algorithm

SAR image after proposed algorithm is shown in Fig 10

Table 1 Accuracy Results for Synthetic Images

Algorithm	Image 1	Image 2	Image 3	Image 4
Fast Unsupervised Bayesian	88.90%	89.60%	96.00%	93.10%
MCMC	94.40%	98.60%	96.10%	98.10%
Iterative ICM	79.50%	18.00%	96.00%	81.50%
Non-iterative ICM	78.40%	60.40%	94.80%	95.60%
Proposed Work	97.70%	98.06%	96.89%	97.35%

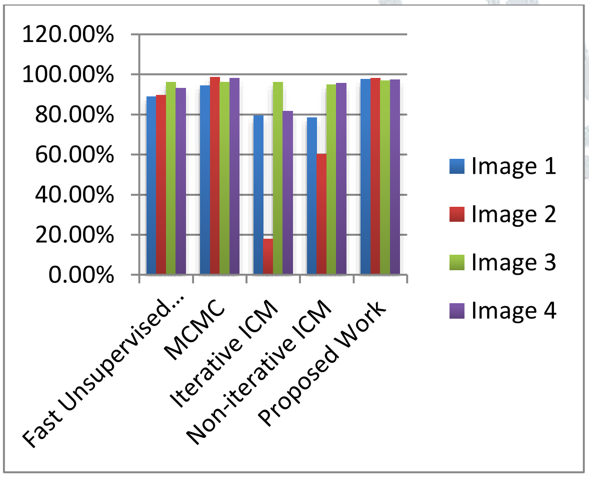


Fig 11 Comparative Analysis of Various algorithms using Segmentation Accuracy

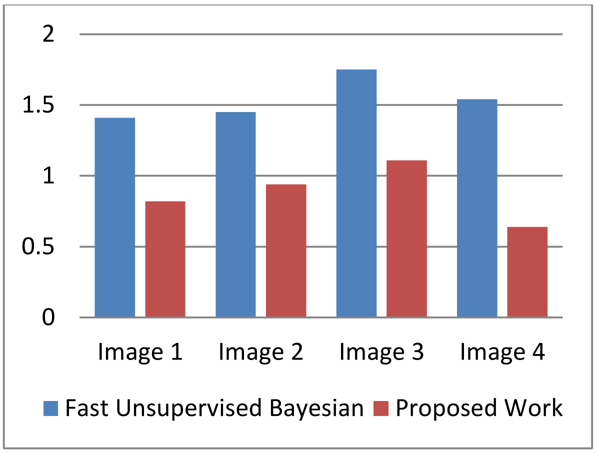


Fig 12 Comparative Analysis of base paper and proposed algorithms using Segmentation Time, other works were removed because of very large time requirements

Table 2 Comparative Analysis of various algorithms using Segmentation Time for real images

Algorithm	Bacteria 1	Bacteria 2	Brain	SAR
Fast Unsupervised Bayesian	0.65	0.8	0.23	0.23
TSA	0.2	0.21	0.17	0.18
Graph-Cut	0.3	0.3	0.21	0.23
Nat. grad.	0.2	0.18	N/A	N/A
FGMA	0.32	0.47	N/A	N/A
MCMC	900	1 150	533	535
Proposed Work	0.35	0.43	0.12	0.12

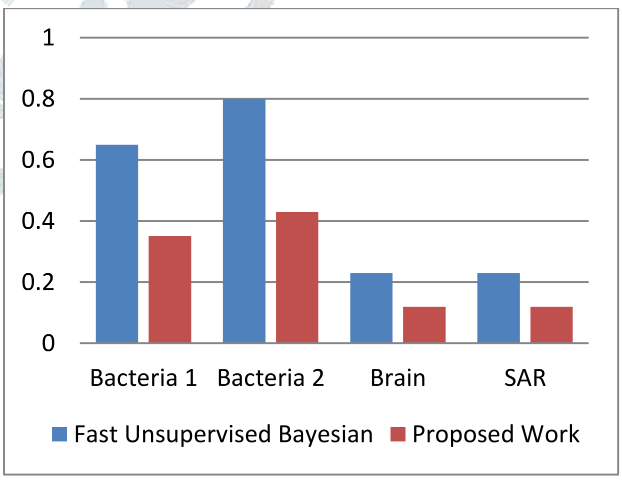


Fig 13Comparative Analysis of various algorithms using Segmentation Time for real images

V. Conclusion

In this paper, we present the study about HMRF and its expectation-maximization algorithm. The basic idea of HMRF is combining "data faithfulness" and "model smoothness", which have very similar nature like active contours, GVF, graph cuts, and random walks. We also combined the HMRF-EM framework with Gaussian mixture models, and applied it to color image segmentation These algorithms are implemented in MATLAB/simulink. . In color image segmentation experiments, we observe that the result obtain from HMRF segmentation are much smoother then the direct k-means clustering. This is because Markov random field imposes strong spatial constraints on the segmented regions, while clustering-based segmentation only considers pixel/voxel intensities. The segmentation time for Bacteria 1 , bacteria 2 , SAR & brain images are 0.35,0.43,0.12 and 0.12 respectively. The accuracy for Bacteria 1 , bacteria 2 , SAR & brain images are 97.70 % , 98.06% , 98.89% and 97.35 % respectively.

There are several future possible researches have to be occur in this fields like to extend its use to non-Gaussian statistical models from a exponential family, here we also consider the linear degradation effects like burring and missing of pixels model selection techniques to determine the segmentation problems in which the number of class is unknown, its further applications to ultrasound technique and its comparison with Bayesian segmentation techniques that are based on alternative HMRF models that can also be solved by convex optimization.

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