IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 3, July 2026

Impact Factor: 8.2

An Efficient Hybrid Segmentation Framework Using Machine Learning Techniques

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Abstract: *Image segmentation is a canonical inverse problem which involves classifying image pixels into clusters that are spatially coherent and have well defined boundaries. It is widely accepted that this task can be formulated as a statistical inference problem and most state-of-the-art image segmentation methods compute solutions by performing statistical inference. In this project, we have studied the hidden Markov random field, and its expectation-maximization algorithm. The basic idea of HMRF is combining "data faithfulness" and "model smoothness", which is very similar to active contours, gradient vector flow (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. In color image segmentation experiments, we can see the HMRF segmentation results are much smoother than the results of 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.*

Keywords: Image segmentation, Bayesian methods, spatial mixture models, Potts Markov random field, convex optimization

I. INTRODUCTION

Owing to the imperfections of image acquisition systems, the images acquired are subject to various defects that will affect the subsequent processing. Although these defects can sometimes be corrected by adjusting the acquisition hardware, for example by increasing the number of images captured for the same scene and adopting higher quality instruments, such hardware-based solutions are time-consuming and costly [1]. Therefore it is preferable to correct the images, after they have been acquired and digitized, by using computer programs, which are fast and relatively low-cost. For example, to remove noise, smooth filters (including linear and median filters) can be applied; to enhance contrast in low-contrast images, the image histograms can be scaled or equalized. Such corrections of defects in images are generally called image pre-processing [2].

After pre-processing, the images are segmented. Segmentation of food images, which refers to the automatic recognition of food products in images, is of course required after image acquisition, because food quality evaluation is completely and automatically conducted by computer programs, without any human participation in computer vision techniques. Although image segmentation is ill-defined, it can generally be described as separating images into various regions in which the pixels have similar image characteristics. Since segmentation is an important task, in that the entire subsequent interpretation tasks (i.e. object measurement and object classification) rely strongly on the segmentation results, tremendous efforts are being made to develop an optimal segmentation technique, although such a technique is not yet available [3]. Nevertheless, a large number of segmentation techniques have been developed. Of these, thresholding-based, region-based, gradient-based, and classification-based segmentation are the four most popular techniques in the food industry, yet none of these can perform with both high accuracy and efficiency across the wide range of different

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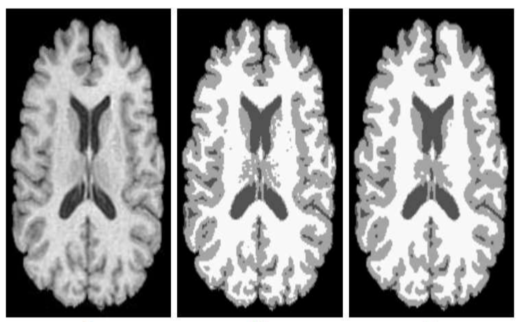
food products. Consequently, other techniques combining several of the above are also being developed, with a compromise on accuracy and efficiency [4].

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.

Markov random field models

Markov random field (MRF) modeling itself is not a segmentation method but a statistical model which can be used within segmentation methods. MRFs model spatial interactions between neighboring or nearby pixels. These local correlations provide a mechanism for modeling a variety of image properties. In medical imaging, they are typically used to take into account the fact that most pixels belong to the same class as their neighboring pixels. In physical terms, this implies that any anatomical structure that consists of only one pixel has a very low probability of occurring under a MRF assumption.

MRFs are often incorporated into clustering segmentation algorithms such as the Kmeans algorithm under a Bayesian prior model. The segmentation is then obtained by maximizing the a posteriori probability of the segmentation given the image data using iterative methods such as iterated conditional modes or simulated annealing. Figure 3c, shows the robustness to noise in a segmentation resulting



(a) (b) (c)

Figure 1 Segmentation of a MR brain image: (a) original image, (b) segmentation using the K-means algorithm, (c) segmentation using the K-means algorithm with a Markov random field prior.

Proposed Algorithm

Markov random fields (MRFs) have been widely used for computer vision problems, such as 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 first proposed for segmentation of brain MR images. For simplicity, we first assume that the image is 2D gray-level, and the intensity distribution of each region to be segmented follows a Gaussian distribution. Given an image Y = (y_1; : : : ; y_N) where N is the number of pixels and each yi is 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 | X,ɵ)P(X)} …………………(1)

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

P(Y | X,ɵ) = $\prod_i P(y_i$ | X,ɵ)…………………(2)

= $\prod_i P(y_i|x_i ɵ_{xi})$, …………….(3)

Where P(y_i | x_i,ɵ$_{xi}$) is a Gaussian distribution with parameters θxi = (μ_{xi}, σ_{xi}), In MRF problems, people usually learn the parameter set ɵ = {θ_l | 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

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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 ɵ 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 ɵ 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:

Start: Assume we have an initial parameter set$ɵ^{(0)}$

E-step: At the ith iteration, we have $ɵ^{(t)}$ and we calculate the conditional expectation:

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

where is the set of all possible configurations of labels.

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

$ɵ^{(t+1)} = \underset{ɵ}{argmax}$ Q(ɵ | $ɵ^{(t)}$) ……………………(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 θl = (μl; σl):

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

We assume that the prior probability can be written as

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

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

P(Y | 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 | 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 | X,$ɵ^{(t)}$)P(X)}

= $\underset{x \in x}{argmin}$ {U (Y | X,$ɵ^{(t)}$) + U (X) }……………(8)

4. Calculate the posterior distribution for all l ∈ L and all pixels y_i using the Bayesian rule:

$P^{(t)}$ (l | 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 | $x_{N_i}^{(t)}$) = $\frac{1}{Z}$ exp (-$\sum_{j \epsilon N_i} V_c$(l,$x_j^{(t)}$) ……………(10)

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

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

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

Result Analysis

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

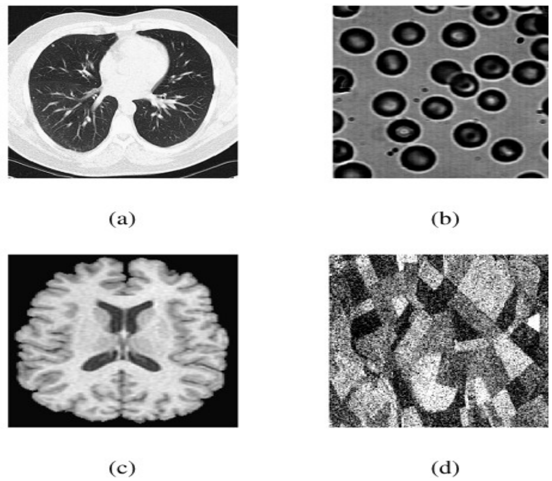

Fig.2. Lungs, Bacteria, Brain and SAR images before segmentation

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

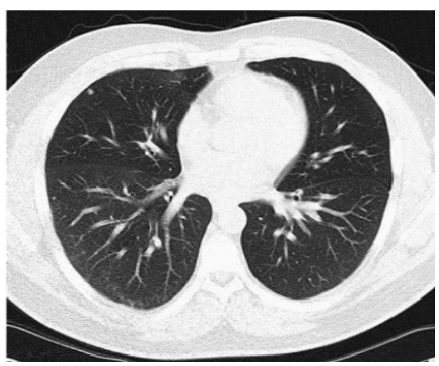

Fig 3 Original Lung Image

The original Lung Image is shown in fig 3.

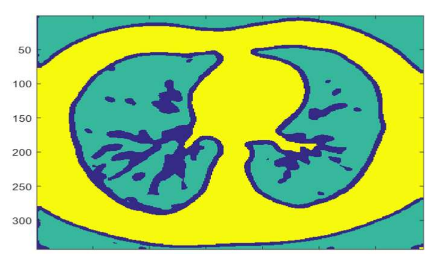

Fig.4.Lung image after proposed algorithm

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

DOI: 10.48175/568

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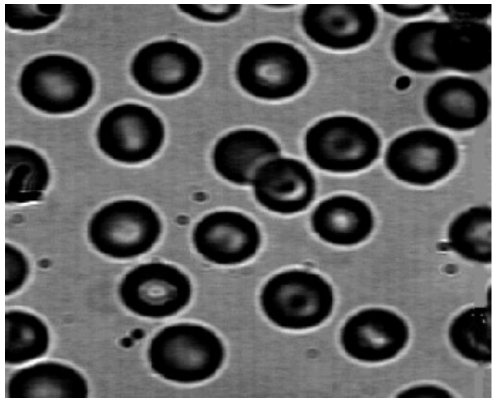

Fig 5 Original Bacteria Image

The original Lung Image is shown in fig 5.

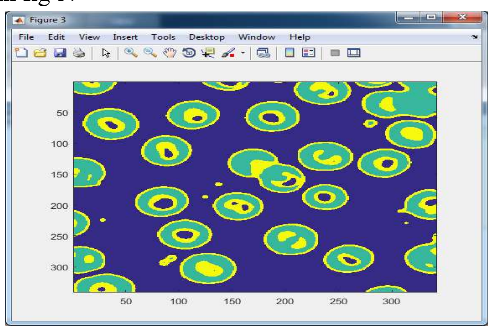

Fig. 6. Bacteria image after proposed algorithm

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

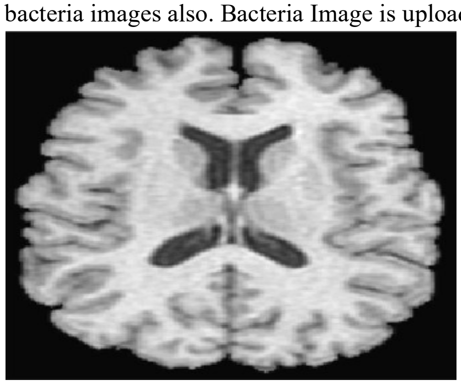

Fig 7 Original Brain Image

The original Brain Image is shown in fig 5.

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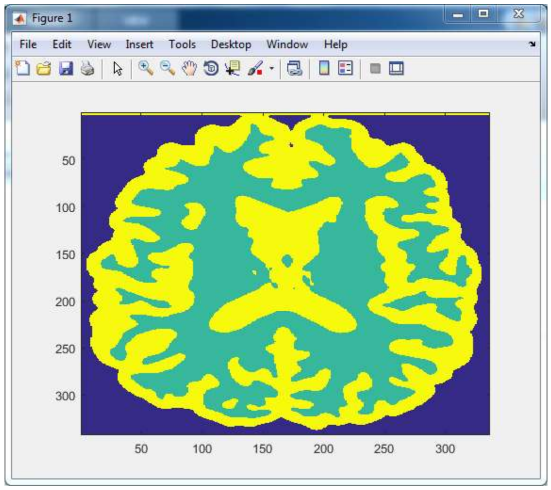

Fig.8. Brain image after proposed algorithm

Brain image after proposed algorithm is shown in Fig 8

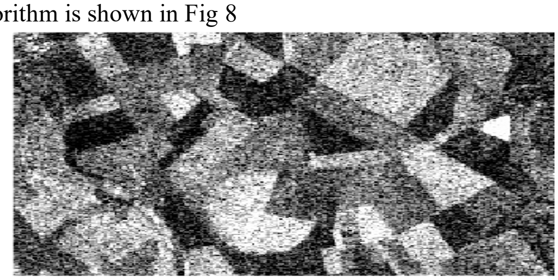

Fig 9 Original SAR Image

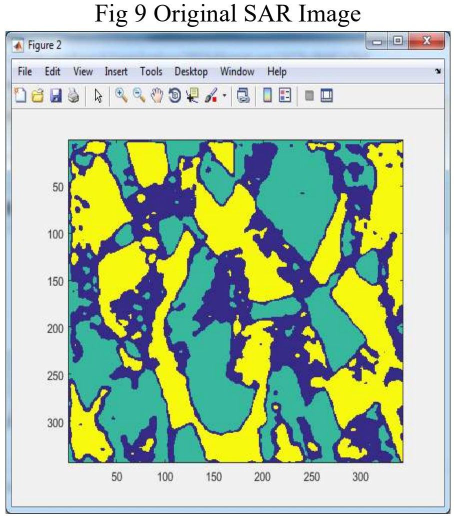

Fig 10 SAR image after proposed algorithm

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%

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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%

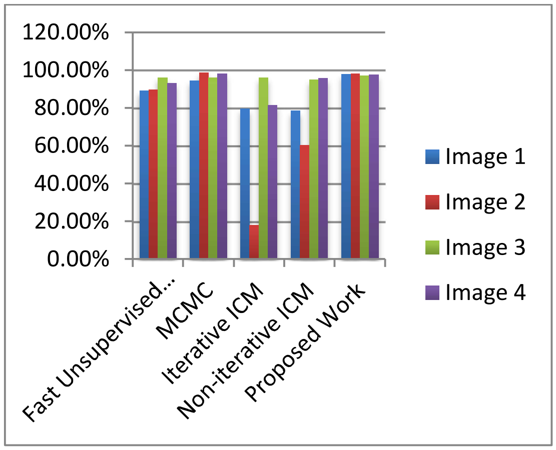

Fig 11 Comparative Analysis of Various algorithms using Segmentation Accuracy

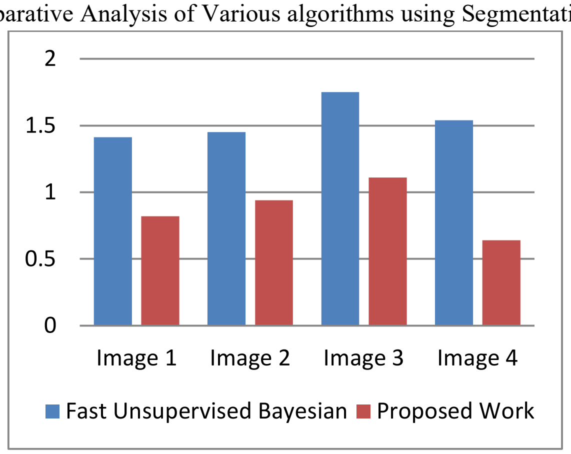

Fig 12 Comparative Analysis of base paper and proposed algorithms using Segmentation Time, other works were removed because of very large time requirements

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

DOI: 10.48175/568

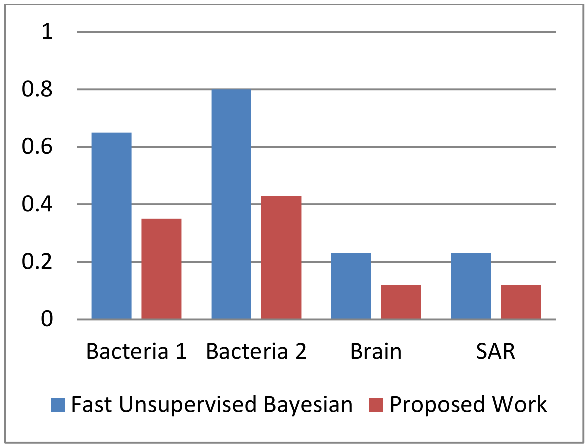

Fig 13 Comparative Analysis of various algorithms using Segmentation Time for real images

II. CONCLUSION

In this paper, we have studied the hidden Markov random field, and its expectation-maximization algorithm. The basic idea of HMRF is combining "data faithfulness" and "model smoothness", which is very similar to active contours, gradient vector flow (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, we can see the HMRF segmentation results are much smoother than the results of 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.

Potential future research topics include the extension of these methods to non-Gaussian statistical models from the exponential family, taking into consideration linear degradation effects such as blurring and missing pixels model choice techniques to address segmentation problems where the number of classes K is unknown, applications to ultrasound and PET image segmentation, and comparisons with other Bayesian segmentation methods based on alternative hidden MRF models that can also be solved by convex optimization.

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DOI: 10.48175/568