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Unsupervised Brain Magnetic Resonance Image Segmentation using HMRF-FCM framework

Smita Pradhan [#1], Dipti Patra [*2]

[#] *Electrical Engg. Department, IPCV Lab, NIT, Rourkela*

[1]ssmita.pradhan@gmail.com

[2]dpatra@nitrkl.ac.in

Abstract—**In this paper, image segmentation of brain magnetic resonance (MR) image is addressed in an unsupervised framework. We propose a novel method considering the hidden Markov random field model (HMRF) to model the image class labels, which takes into account the mutual influences of neighbouring sites formulated on the basis of fuzzy clustering principle. By introducing the effective means to incorporate the explicit assumptions of the HMRF model into fuzzy clustering procedure, an efficient fuzzy clustering- type treatment is yielded. This combines the benefits from the spatial coherency modelling capabilities of the HMRF model, and the enhanced flexibility obtained by the fuzzy clustering algorithm, i.e. fuzzy c-means algorithm (FCM). The proposed HMRF-FCM segmentation framework is validated with noisy synthesis as well as brain MR images. We experimentally demonstrate the superiority of the proposed approach over the existing HMRF-EM framework applied to brain MR image segmentation.**

Keywords— **Segmentation, magnetic resonance image, Markov random field model, hidden Markov random field model, fuzzy c-means clustering.**

I. Introduction

The problem of image segmentation has attracted the attention of the researchers for quite some time. The problem has been addressed in both deterministic and stochastic framework. In stochastic domain, Markov Random Field (MRF) model has been extensively used as the image models [1, 2, 3]. The segmentation problem is also addressed as supervised and unsupervised image segmentation. When the number of classes, the image labels and the image model parameters are assumed to be unknown, the problem is viewed as an unsupervised problem.

Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. Segmentation of MR images into different tissue classes, especially grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF) is an important task. Accurate and robust brain tissue segmentation from magnetic resonance (MR) images is key issue in many applications of medical image analysis for quantitative studies and particularly in the study of several brain disorders. A wide variety of approaches have been proposed for brain MR image segmentation [4, 5].

For unsupervised brain MR image segmentation, hidden Markov random field (HMRF) has been proposed by Zhang *et. al*, to model the observed image [4]. This model, which is a stochastic process generated by a MRF whose state sequence can not be observed directly but, can be indirectly estimated through observations. The observed sequences are stochastic function of hidden sequences. The importance of HMRF model derives from the MRF theory, in which the spatial information of an image is encoded through contextual constraints of neighbouring pixels. In [4], the image labels are obtained using the MAP criterion and the model parameters are the maximum likelihood (ML) estimates. The model parameters as well as class labels are estimated using Expectation–Maximization (EM) algorithm. Even though HMRF-EM provides reasonable segmentation results, it has been shown that it leads to biased parameter estimates.

Cluster analysis is a methodology developed for capturing local substructures in multivariate data by applying an affinity criterion to group data points. A significant aspect of cluster analysis with increasing complexity is the rigidity (crispness) of the partition. Many authors have proposed a setting based on fuzzy set theory [6] as the appropriate approach to cope with this problem. During the last decades, fuzzy clustering methodologies, especially the fuzzy *c*-means algorithm (FCM), have been widely applied as the effective means to conduct image segmentation [7, 8]. Although the FCM algorithm usually performs well with noise-free images, it obtains a rather poor result when having to deal with images corrupted by noise, and other imaging artifacts, as is often the case with real-world images [9, 10]. Various more robust alternatives for the dissimilarity function of the FCM algorithm have been proposed. However, a major shortcoming of these methods, in terms of the image segmentation task, is that they do not take into account the spatial dependencies between the clustered data [11].

In this paper, a novel, fuzzy regard toward the HMRF model is proposed for brain MR image segmentation. By introducing the effective means to incorporate the explicit assumptions of the HMRF model into the fuzzy clustering procedure, an efficient fuzzy clustering-type treatment is yielded. The proposed approach is formulated using an HMRF-FCM algorithm which offers an FCM-type treatment of the HMRF model. This combines the benefits from the spatial coherency modelling capabilities of the HMRF model, and the enhanced flexibility obtained by the fuzzy clustering algorithm.

II. Hidden Markov random field model

A special case of a hidden Markov model (HMM) where the underlying stochastic process is a MRF is referred to as

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hidden Markov random field model. 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 neighbourhood system η and is described by its local characteristics. Since X is a MRF, or equivalently Gibbs distributed, the joint distribution can be expressed as

$$P(X = x \mid \beta) = \frac{1}{W(\beta)} \exp(-U(x,\beta))$$

where $W(\beta) = \sum_{x \in X} \exp(-U(x,\beta))$ is the partition function, β denote the clique parameter vector, $U(x,\beta)$ is the energy function and is of the form $U(X,\beta) = \sum_{c \in C} V_c(x,\beta)$, $V_c(x,\beta)$ is the clique potential. C is the class of subsets of the sites. Let Y denote the random field associated with the observed image. For any realization of the considered pixel x, the random variables Y_j are conditional independent, i.e

$$P(Y \mid X) = \prod_{j=1}^{s} P(y_j \mid x_j) \tag{1}$$

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

$$P(Y,X) = P(Y \mid X)P(X) = P(X)\prod_{j=1}^{s} P(y_j \mid x_j)$$

According to the local characteristics of MRF, the joint probability distribution of pair (X_j, Y_j) given the neighbourhood configuration of X_{η_j}

$$P(y_j, x_j \mid x_{\eta_j}) = P(y_j \mid x_j) P(x_j \mid x_{\eta_j}) \tag{2}$$

Thus, the marginal probability distribution of Y_j dependent on θ and X_{η_j} can be expressed as

$$P(y_j \mid x_{\eta j}, \theta) = \sum_{l \in L} P(y_j, l \mid x_{\eta j}, \theta) \tag{3}$$

where $\theta = \{\theta_l, l \in L\}$. (3) is the hidden Markov random field model, θ_l is the set of model parameters, l denotes the number of labels, L is the set of all class labels. The conditional distributions of the observed variables given the HMRF states they are emitted from, $p(y_j|x_j)$, are taken to be of multivariate Gaussian form, that is

$$P(y_j \mid x_j, \theta_{x_j}) = N(y_j \mid \mu_{x_j}, \sigma_{x_j}) \tag{4}$$

where μ_{x_j} and σ_{x_j} are the mean and covariance matrix of the emission distribution of the x_j^{th} hidden state of the HMRF model.

III. Fuzzy C-Means Clustering

Clustering is an exploratory data analysis method applied to data in order to find structure or certain grouping in a data set. Fuzzy clustering accepts the fact that the clusters or classes in the data are usually not completely well separated and thus assigns a membership degree between 0 and 1. The most common fuzzy clustering techniques aim at minimizing an objective function. Let us consider the problem of clustering s multivariate data points into q clusters. In the standard FCM algorithm [8], the fuzzy objective function to be minimized is given by

$$J_\phi \cong \sum_{i=1}^{q} \sum_{j=1}^{s} r_{ij}^{\phi} d_{ij} \tag{5}$$

where $\phi \geq 1$ is a weighting exponent on each fuzzy membership function r_{ij}, is called the fuzzifier of the clustering algorithm. d_{ij} is the dissimilarity function. Ichihashi *et al*. provided another FCM variant, introducing a regularization by KL information [12]. Under this consideration, the fuzzy objective function becomes

$$J_\lambda = \sum_{i=1}^{q} \sum_{j=1}^{s} r_{ij} d_{ij} + \lambda \sum_{i=1}^{q} \sum_{j=1}^{s} r_{ij} \log\left(\frac{r_{ij}}{\pi_{ij}}\right) \tag{6}$$

where π_i is the prior probability (weight) of the i^{th} cluster. The parameter λ is the model's degree of fuzziness of the fuzzy membership values.

IV. Proposed Approach

A. HMRF-FCM framework

The HMRF model can be viewed as representing a cluster formulated in the space Y of observable data. The *a posteriori* probability of the observation y_j, associated with the j^{th} site, deriving from the cluster represented by the i^{th} model state is $p(x_j = i|y_j)$. It holds

$$0 \leq p(x_j = i \mid y_j) \leq 1, \quad \sum_{i=1}^{q} p(x_j = i \mid y_j) = 1 \tag{7}$$

where $(i = 1, \ldots, q, j = 1, \ldots, s)$. The HMRF model can be regarded as defining a fuzzy q-partition of the observations space Y. We denote this fuzzy partition as

$$R = \{r_{ij}\} \tag{8}$$

where r_{ij} $(i = 1, \ldots, q, j = 1, \ldots, s)$ represents the degree of the observable vector y_j belonging to the cluster represented by the i^{th} state of the HMRF model. The function r_{ij} is called the fuzzy membership function and has the following properties:

$$0 \leq r_{ij} \leq 1, \quad \sum_{i=1}^{q} r_{ij} = 1, \quad 0 \leq \sum_{j=1}^{s} r_{ij} < s \tag{9}$$

HMRF oriented fuzzy modification objective function (6) is given by

$$Q_\lambda = \sum_{i=1}^{q} \sum_{j=1}^{s} r_{ij} d_{ij} + \lambda \sum_{i=1}^{q} \sum_{j=1}^{s} r_{ij} \log\left(\frac{r_{ij}}{\pi_{ij}}\right) \tag{10}$$

where the dissimilarity function d_{ij} of the algorithm is the negative log-likelihood of the i^{th} model state with respect to the j^{th} fitting observation, i.e.,

$$d_{ij}(\theta_i) = -\log p(y_j \mid x_j = i; \theta_i)$$

In (10), π_{ij}' s are the point wise prior probabilities of the HMRF model states, obtained on the basis of the mean-field-like approximation of the MRF

$$\pi_{ij} = p(x_j = i \mid \hat{x}_{\partial_j}; \beta) = \frac{\exp\left(-\sum_{c \in j} V_c(\tilde{x}_{ij} \mid \beta)\right)}{\sum_{h=1}^{q} \exp\left(-\sum_{c \in j} V_c(\tilde{x}_{hj} \mid \beta)\right)} \tag{11}$$

and $\tilde{x}_{ij}^{(k)} = \left(x_j = i, x_{\partial_j}^{(k)}\right)$. $x_{\partial_j}^{(k)}$ is the current estimate of j^{th} pixel. Eventually, the objective function of the proposed approach becomes

$$Q_\lambda(\psi) = -\sum_{i=1}^{q}\sum_{j=1}^{s} r_{ij} \log p\left(y_j \mid x_j = i; \theta_i\right) + \lambda \sum_{i=1}^{q}\sum_{j=1}^{s} r_{ij} \log\left(\frac{r_{ij}}{\pi_{ij}}\right) \quad (12)$$

where $\boldsymbol{\psi} = \{\theta, \beta\}$ and $p(y_j \mid x_j = i; \theta_i)$ is given by (4).

B. Model Parameter Estimation

Minimization of the fuzzy objective function $Q_\lambda(\psi)$ is done in proposed HMRF-FCM framework for estimation of HMRF model parameters by a given model fitting dataset. The estimate $\hat{x}^{(k)}$ of the site labels vector on the k^{th} iteration of the algorithm is obtained iteratively by defuzzification of the computed fuzzy memberships $r_{ij}^{(k)}$. Attributing each site to the MRF state and maximizing its fuzzy membership function is expressed as

$$\hat{x}_j^{(k)} = \arg\max_{i=1}^{q} r_{ij}^{(k)} \quad (13)$$

The estimation of the fuzzy membership functions $r_{ij}^{(k)}$ is obtained as

$$r_{ij}^{(k+1)} = \frac{\pi_{ij}^{(k)} \exp\left(-\frac{1}{\lambda} d_{ij}^{(k)}\right)}{\sum_{h=1}^{q} \pi_{hj}^{(k)} \exp\left(-\frac{1}{\lambda} d_{hj}^{(k)}\right)} \quad (14)$$

where

$$d_{ij}^{(k)} = \frac{w}{2}\log(2\pi) + \frac{1}{2}\log\left|\sigma_i^{(k)}\right| + \frac{1}{2}\left(y_j - \mu_i^{(k)}\right)^T \sigma_i^{(k)^{-1}}\left(y_j - \mu_i^{(k)}\right) \quad (15)$$

The estimation of the μ_i , σ_i in (15)are updated as

$$\mu_i^{(k+1)} = \frac{\sum_{j=1}^{s} r_{ij}^{(k)} y_j}{\sum_{j=1}^{s} r_{ij}^{(k)}} \quad (16)$$

$$\sigma_i^{(k+1)} = \frac{\sum_{j=1}^{s} r_{ij}^{(k)}\left(y_j - \mu_i^{(k)}\right)\left(y_j - \mu_i^{(k)}\right)^T}{\sum_{j=1}^{s} r_{ij}^{(k)}} \quad (17)$$

The proposed HMRF-FCM algorithm for the fuzzy treatment of the HMRF model comprises the following steps.

1) Derive an estimation of $x^{(k)}$ using (13).
2) Using $x^{(k)}$, compute the point wise prior probabilities of the MRF $\pi_{ij}^{(k)}$ given by (11).
3) Compute the fuzzy membership functions $r_{ij}^{(k)}$ using (14).
4) Compute the estimator updates $\mu_{ij}^{(k+1)}$ and $\sigma_{ij}^{(k+1)}$ by (16) and (17) respectively.
5) In case of convergence, i.e.

$$\left|Q_\lambda\left(\psi^{(k+1)}\right) - Q_\lambda\left(\psi^{(k)}\right)\right| / Q_\lambda\left(\psi^{(k)}\right) < T_c ,$$

Where T_c is the convergence threshold, exit ; otherwise $k = k + 1$ and return to 1.

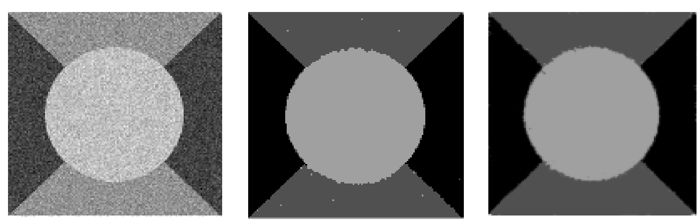
V. SIMULATION AND RESULTS

We have considered both synthetic and brain MR images in our simulations. We adopt a first order neighbourhood system with the energy function given by

$$U(x \mid \beta) = -\beta \sum_{j \in S} \sum_{l \in \partial_j} \delta\left(x_j - x_l\right)$$

where $$\delta\left(x_j - x_l\right) = \begin{cases} 1, & if\ x_j = x_l \\ 0, & otherwise \end{cases}$$

This energy function is employed to evaluate the HMRF-FCM algorithm. Our proposed HMRF-FCM algorithm is used to segment the noisy synthetic as well as brain MR images. The synthetic three class noisy image of size (128x128) with SNR 20dB is shown in Fig 1(A). The initial values of the parameters corresponding to these classes are presented in Table 1. The initial parameters (μ_i , σ_i) were selected from histogram of the noisy image. The value of λ is taken as 1. The model parameters and image labels are recursively estimated for all the classes and eventually the algorithm converges to stable labelization. The segmented images obtained using HMRF-EM framework proposed in [4] and HMRF-FCM framework are as shown in Fig 1(B) and (C) respectively. It is observed that the number of misclassified pixels in Fig 1(B) is much more than that of Fig. 1(C). The converged value of model parameters (μ_f , σ_f) are shown in Table 1. The mis-classification error (MCE) in case of HMRF-EM and HMRF-FCM framework is found to be 2.97% and 1.89% respectively. The performance study on visual as well as quantitative measure shows that HMRF-FCM improves the accuracy of brain MRI segmentation due to the combined benefits of FCM and HMRF model.



(A) SYNTHETIC 3 CLASS ORIGINAL IMAGE (B) SEGMENTED IMAGE USING HMRF-EM (C) SEGMENTED IMAGE USING HMRF-FCM

Fig 1: Segmentation of synthetic image of size (128x128) with SNR=20db

TABLE I. Parameters for Fig. 1

Class	1	2	3	Framework	MCE %
μ_i	0.512	1.175	1.825		
σ_i	0.293	0.549	0.580		
μ_f	0.829	1.817	2.377	HMRF-EM	2.97
σ_f	0.169	0.172	0.186		
μ_f	0.771	1.79	2.051	HMRF-FCM	1.89
σ_f	0.019	0.038	0.039		

The proposed model is also validated with a brain magnetic resonance image of size (128x128) as shown in Fig. 2(A). The image is segmented using both HMRF-EM and HMRF-FCM model and the segmented images are depicted in Fig. 2(B) and (C) respectively. The initial and final values of model parameters are shown in Table 2. The initial no. of classes are considered to be five. It is observed in Fig 2(B) that the segmented image using HMRF-EM framework is converged to four classes except the background. This is due to the local convergent ICM algorithm in Expectation step. The percentage of misclassification error is 19.45%.

(A) NOISY IMAGE OF SNR=22DB (B) SEGMENTED IMAGE USING HMRF-EM (C) SEGMENTED IMAGE USING HMRF-FCM

Fig. 2: Segmentation of Brain MR image of size (128x128)

In Fig 2(C), it is observed that the segmented image using HMRF-FCM framework is converged to three classes, i.e. grey matter, white matter and cerebrospinal fluid. The percentage of misclassification error is only 8.07%.

TABLE III : Parameters for Fig. 2

Class	1	2	3	4	Framework	MCE %
μ_i	0.01	0.96	1.76	2.93		
σ_i	0.22	0.60	0.56	0.37		
μ_f	0.01	0.72	1.93	2.78	HMRF-EM	8.07
σ_f	0.05	0.10	0.09	0.02		
μ_f	0.07	1.57	2.52	4.17	HMRF-FCM	19.45
σ_f	0.03	0.08	0.07	0.01		

It is further observed that in HMRF-EM framework, the model parameters converge in 3 iterations with computational time around 4 secs. But in HMRF-FCM framework, the model parameters converge only after1 iteration. This is due to the benefits of fuzzy c-means clustering approach in HMRF model. From our experiment on segmentation of both synthetic as well as brain MR images, it is observed that the proposed HMRF-FCM framework outperforms the existing popular HMRF-EM framework on the basis of misclassification error and convergence time. The proposed technique can be applied successfully to brain magnetic resonance image segmentation in automatic mode.

VI. CONCLUSION

In this paper, we have addressed the segmentation of brain MR images in an unsupervised framework. The HMRF model is used to model the image class labels. This model takes care of the mutual influences among neighboring sites in spatial domain. A novel method is proposed by incorporating the fuzzy clustering type treatment of hidden Markov random field model. This HMRF-FCM framework is effected by considering a fuzzy objective function with a suitable dissimilarity function selection based on MRF distribution. The HMRF-FCM algorithm combines the advantages of HMRF model, in terms of spatially correlated data clustering effectiveness, and the increased flexibility of FCM-type method. The proposed method provides a significant enhancement for the brain MR image segmentation into tissue classes. It outperforms the existing EM type regards of the HMRF model in terms of less misclassification error, faster convergence and better accuracy. Hence, the proposed HMRF-FCM framework can be successfully applied in automatic mode for brain MR image segmentation. The future work may be extended for segmentation of cancer tissues in different magnetic resonance images.

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