Constrained Compound Markov Random Field Model for Segmentation of Color Texture and Scene Images

Sucheta Panda
IPCV Lab., Department of Electrical Engineering,
National Institute of Technology,
Rourkela-769008, Orissa, India
Email: sucheta_panda@rediffmail.com

P.K.Nanda
Department of Electronics and Telecommunication Engineering,
C.V Raman College of Engineering,
Bhubaneswar-752054,Orissa,India.
Email: pknanda_d13@rediffmail.com

Rahul Dey
IPCV Lab., Department of Electrical Engineering,
National Institute of Technology,
Rourkela-769008, Orissa, India
Email: rahuldey@rediffmail.com

***Abstract*— In this paper, we propose a constrained compound Markov random Field Model (MRF) to model color texture as well as scene images. Ohta (I_1, I_2, I_3) color model is used as the color model for segmentation. Besides, intra plane model, the constrained model is modified to take care of inter-plane interaction as well. Hence, the model is called as Double Constrained Compound MRF (DCCMRF) model. The problem is formulated as pixel labelling problem and the pixel labels are estimated using Maximum a posteriori (MAP) criterion.The MAP estimates are obtained using hybrid algorithm. The DCCMRF model exhibited improved segmentation accuracy as compared to DCMRF, MRF, Double MRF (DMRF), Double Gauss MRF(DGMRF) and JSEG method. The proposed models have been successfully tested for two,four and five class problem.**

I. Introduction

Image segmentation is a basic early vision problem which serves as precursor to many high level vision problems. Color image segmentation provides more information while solving high level vision problems such as, object recognition, shape analysis etc. Therefore, the problem of color image segmentation has been addressed more vigorously for more than one decade. Different color models such as $RGB, HSV, YIQ, Ohta(I_1, I_2, I_3), CIE(XYZ, Luv, Lab)$ are used to represent different colors [1]. From the reported study, HSV and I_1, I_2, I_3 have been extensively used for color image segmentation. Ohta color space is a very good approximation of the Karhunen-Loeve transformation of the RGB found by decorrelation of RGB components, which makes it very suitable for many image processing applications [2].

In model based approach, the accuracy of the segmented image greatly depends upon the use of appropriate image model. Stochastic models, particularly MRF models, have been successfully used as the image model for image restoration and segmentation[3]. Often, the segmentation problem is cast using MAP criterion and the MAP estimates are obtained by Simulated Annealing(SA) algorithm[4]. MRF model has also been successfully used as the image model while addressing the problem of color image segmentation both in supervised and unsupervised framework[6],[5]. Hidden Markov Random Field(HMRF) has also been employed for color image segmentation in unsupervised framework [7]. In order to take into account the dependencies of the color planes as well as the interactions across the scales, [8] have proposed a wavelet domain hidden markov model (WDHMM) which has yielded a promising results for color texture. Recently, Gaussian Mixture Model (GMM) have been proposed to model color textures on various feature spaces for image segmentation[10],[9].

In this work, a new model known as the Constrained MRF(CMRF)model is proposed to model natural scenes and color textures. The ohta(I_1, I_2, I_3) model is used as the color model. The constrained MRF model is extended to take care if intra-plane as well as inter-plane interactions. Thus, called Double Constrained Compound MRF Model (DCCMRF). The problem is formulated as a pixel labelling problem and the observed image is assumed to be the degraded version of the original image labels. This degradation is assumed to be Gaussian process. The image label estimation problem is cast in MAP framework. A hybrid algorithm is proposed to obtain the MAP estimates. The CMRF model parameters are selected on trial and error basis. The double constrained compound MRF model is found to yield better results as compared to constrained model and JSEG method[11].The performance of the Hybrid algorithm is compared with that of SA and it is found that the hybrid algorithm converges faster than that of SA. The proposed CMRF model and DCMRF model are found to model the scene images as well as the color textures effectively. The DCMRF model has a unifying property of modelling both natural scenes and texture images from the vision texture (VisTex) database of MIT and Berkeley Segmentation Dataset. The proposed model and the algorithm could be successfully tested for two,four and five class problems.

II. Double MRF model

Capturing salient spatial properties of an image leads to the development of image models. MRF theory provides a convenient and consistent way to model context dependent entities for eg. image pixels and correlated features [12]. Though the MRF model takes into account the local spatial interactions, it has its limitations in modeling natural scenes of distinct regions. In case of color models, it is known that there is a correlation among the color components of RGB model. In our formulation, we have decorrelated the color components and introduced a interaction process to improve the segmentation accuracy. We have employed inter-color-plane interaction (Ohta(I_1, I_2, I_3) color model)process which reinforces partial correlation among different color components.

We assume all images to be defined on discrete rectangular lattice M1 x M2. Let Z denote the label process corresponding to the segmented image and z is a realization of the label process i.e the segmented image. The observed image X is assumed to be a random field that is assumed to be the degraded version of the label process Z and this degradation process is assumed to be Gaussian process W. The label process Z in a given plane is assumed to be MRF. The a priori model takes care of inter as well as intra color plane interactions. The prior probability distribution of z is constructed with clique potential function corresponding to intra-color plane interactions, for example I_1 and another clique potential function with interplane interactions (for example between I_1 and I_2). The process of inter color plane interactions are shown in Figure1. Thus X is a compound MRF. MRF model taking care of both inter as well as intra plane interactions. It is known that if Z is assumed MRF, then the prior probability distribution $P(Z = z)$ is Gibb's distributed that can be expressed as $P(Z = z|\theta) = \frac{1}{Z'} e^{-U(z,\theta)}$, where $Z' = \sum_z e^{-U(z,\theta)}$ is the partition function, θ denotes the clique parameter vector, the exponential term $U(z, \theta)$ is called the energy function and is of the form $U(z, \theta) = \Sigma_{c \in C} V_c(z, \theta)$, with $V_c(z, \theta)$ being referred as the clique potential function. Since the inter-plane process is viewed to be MRF, we know that $P(Z^{I_2}_{i,j} = z^{I_2}_{i,j} | Z^{I_1}_{k,l} = z^{I_1}_{k,l}, (k, l) \neq (i, j), \forall (k, l) \in I_1,) = P(Z^{I_2}_{i,j} = z^{I_2}_{i,j} | Z^{I_1}_{k,l} = z^{I_1}_{k,l}, (k, l) \neq (i, j), (k, l) \in \eta^{I_1}_{i,j})$, Where I_1 and I_2 denotes I_1 and I_2 color planes respectively. In other words a pixel in one plane (say for e.g I_1-plane) is assumed to have interaction with pixels of I_2 and I_3 planes, the interaction process of each color plane is shown in Fig 1(a). For the sake of illustration, the interaction of $(i, j)^{th}$ pixel in I_2 plane with the neighboring pixels of I_1 plane for a first order neighborhood system is also depicted in Fig.1(b). The observed image X which is assumed to be MRF is considered as the degraded version of the label process and hence consists of Z and W. The model parameters for both intra and inter color plane processes are selected on an trial and error basis. The Weak membrane model [3] is considered to model the intra as well as inter plane clique potential functions. For example, the weak membrane model for interplane interaction process for two color components, (I_2 and I_1) (as shown in Fig.1(b)) can be expressed as $V_c(z^1) = \alpha\{(n^{I_2}_{i',j'} - n^{I_1}_{i-1,j})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i,j-1})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i,j+1})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i+1,j})^2\}$, where α is the MRF internal field parameter. Superscripts I_1 and I_2 corresponds to I_1-plane and I_2-plane respectively.

A. Constrained MRF Model

MRF model takes care of the local spatial interactions, nevertheless it has limitation in modeling natural scenes. In the following we propose new model with a view to take care of intra as well as inter plane interactions. In this research work, we employed the notion of martingale to reinforce the local dependence. Let $Z_1, Z_2, \cdots, Z_n$ be the random variables associated with the image of size $L = M1$ x $M2$ and let these form a martingale sequence. Each pixel can assume a label from the set of labels $\{0 - L\}$. Therefore, $E[Z_{i,j}/Z_{k,l}, k, l \neq i, j] = Z_{i-1,j}$ for any $k, l \in \eta_{i,j}$, where $\eta_{i,j}$ is the neighborhood of (i, j).

Assuming further that Z is a Markov process, we have

$$E[Z_{i,j} \mid Z_{k,l}, k, l \neq i, j] = \sum_{z_{i,j} \in L} z_{i,j} \frac{P(Z = z)}{\sum_{z_{i,j}} P(Z = z)} \quad (1)$$

For a specific case, (1) can be expressed as,

$$z_{i-1,j} = \sum_{z_{i,j} \in L} z_{i,j} \frac{e^{-U(Z)}}{\sum_{z_{i,j} \in L} e^{-U(Z)}}$$

Instead of taking the pixel $z_{i-1,j}$, we take the average of the neighborhood pixels as $z_{i,j_{avg}}$. This local dependence is added to the clique potential functions of the prior model. The energy function in terms of the clique potential functions can be expressed as the following equation (4). By and large, the pixel labelling problem is formulated using Maximum a Posteriori (MAP) criterion. With the label process modeled as MRF and the assumed degradation process as Gaussian, the MAP estimation problem reduces to the following form

$$\hat{z} = \underset{z}{min} \sum_{i,j} U_{i,j}(z_{i,j}, \theta) \quad (2)$$

$$U(z, \theta) = \sum_{c \in C} V_c(z_{i,j}, \theta) \quad (3)$$

In order to reinforce local dependency, the above minimization problem is modified to be a constraint minimization. The constraint minimization problem can be stated as follows

$$\hat{z} = \underset{z}{min} \sum_{i,j} U_{i,j}(z_{i,j}, \theta) \quad (4)$$

Subject to the constraint

$$z_{i,j_{avg}} = \sum_{z_{i,j} \in L} z_{i,j} \frac{e^{-U(Z)}}{\sum_{z_{i,j} \in G} e^{-U(Z)}}$$

Hence, using Lagrange multiplier λ, this constraint minimization problem reduces to the following

$$\min_z \sum_{i,j} U(z_{i,j}) + \lambda \left\{ z_{i,j_{avg}} - \sum_{z_{i,j} \in L} z_{i,j} \frac{e^{-U(Z)}}{\sum_{z_{i,j} \in L} e^{-U(Z)}} \right\}^2 \quad (5)$$

Where, $U(z_{i,j})$ is *a posteriori* energy of weak membrane model and λ is selected depending on type of scene image. For scene images λ is selected at a low value and for large size texture images λ is set a high value. Because the second term of (5) is an additional constraint in the clique potential, we name this model as the Constrained MRF(CMRF) model.

B. Double Compound Constrained MRF model

We also extended the local reinforcement to the inter-plane interactions and hence introduce the notion of constrained model in the interplane interactions. Thus, there is one clique potential corresponding to intra-plane interactions and another clique potential function corresponding to inter-plane interactions. In the line of the constrained model according to (5) is now applied to intra as well as inter color plane processes. The constrained condition is among I_1-I_2,I_2-I_3 and I_3-I_1 color planes. The energy function for double constrained model in the line of (5) can be expressed as follows.

$$\begin{aligned}\min_{z}\sum_{i,j}U(z_{i,j}^{I_1})+\lambda\left\{z_{i,j_{avg}}^{I_2}-\sum_{z_{i,j}\in L}z_{i,j}^{I_1}\frac{e^{-U(Z^{I_1})}}{\sum_{z_{i,j}\in L}e^{-U(Z^{I_1})}}\right\}^2\\ +U(z_{i,j}^{I_2})+\lambda\left\{z_{i,j_{avg}}^{I_3}-\sum_{z_{i,j}\in L}z_{i,j}^{I_2}\frac{e^{-U(Z^{I_2})}}{\sum_{z_{i,j}\in L}e^{-U(Z^{I_2})}}\right\}^2\\ +U(z_{i,j}^{I_3})+\lambda\left\{z_{i,j_{avg}}^{I_1}-\sum_{z_{i,j}\in L}z_{i,j}^{I_3}\frac{e^{-U(Z^{I_3})}}{\sum_{z_{i,j}\in L}e^{-U(Z^{I_3})}}\right\}^2\end{aligned} \tag{6}$$

Where

$$U(I_1)=\sum_{i,j}U(z_{i,j}^{I_1})+ \lambda\left\{z_{i,j_{avg}}^{I_2}-\sum_{z_{i,j}\in L}{z_{i,j}}^{I_1}\frac{e^{-U(Z^{I_1})}}{\sum_{z_{i,j}\in L}e^{-U(Z^{I_1})}}\right\}^2 \tag{7}$$

and analogously $U(I_2)$ and $U(I_3)$ can be defined.

III. Image Segmentation

The segmentation problem is cast as the pixel labelling problem. Each pixel can assume a label from the set of labels $\{0-L\}$. In a given image of size $L = M1$ x $M2$, let $Z_{i,j}$ denote the random variable for $(i,j)^{th}$ pixel, $\forall (i,j) \in L = M1$ x $M2$. Z denotes the label process and z denotes a realization of the process. The label estimates $\hat{z}$ is obtained by maximizing the posterior probability $P(Z = z|X = x, \theta)$. Thus, the optimality criterion can be expressed as follows,

$$(\hat{z}) = \underset{z}{arg\,max}\ P(Z=z|X=x,\hat{\theta}) \tag{8}$$

where, $\hat{\theta}$ denotes the associated parameter vector of the double MRF model Z.

$$(\hat{z}) = \underset{z}{arg\,max}\ P(Z=z|X=x,\hat{\theta}) \tag{9}$$

Since z is unknown, $P(Z = z|X = x, \hat{\theta})$ in (2) can not be computed. Using Bayes's theorem, $P(Z = z|X = x, \hat{\theta})$ can be expressed as

$$P(Z=z|X=x,\hat{\theta}) = \frac{P(X=x|Z=z,\theta)P(Z=z)}{P(X=x|\theta)} \tag{10}$$

The observed image X is given and hence the denominator $P(X = x|\theta)$ of (10) is a constant quantity. $P(Z = z)$ is the *a priori* probability distribution of the labels. The image model considered is

$$Y_{ij} = Z_{ij} + W_{ij}, \quad \forall\,(i,j) \in (M1 \times M2) \tag{11}$$

which with a lexicographical ordering will be $Y = Z + W$.We make the following assumptions: (a) $W_{i,j}$ is a white Gaussian sequence with zero mean and variance σ^2. (b) $W_{i,j}$ is statistically independent of $Z_{k,l}$, for all (i,j) and (k,l) belonging to $M1 \times M2$. (c) $z_{i,j}$ takes any value from the label set $M = (1, \ldots, M_m)$, (typically $M_m = 256$). The degradation process is assumed to be Gaussian and hence $P(X = x|Z = z, \theta)$ of (10) can be written as $P(X = x|Z = z, \theta) = P(X = z + w|Z, \theta) = P(W = x - z|Z, \theta)$. Since, W is a Gaussian process, and there are three spectral components present in a color image, we have,

$$P(W=x-z|Z,\theta)=\frac{1}{\sqrt{(2\pi)^n det[\bar{\mathbf{K}}]}}e^{-\frac{1}{2}(\mathbf{x}-\mathbf{z})^{\mathbf{T}}\bar{\mathbf{K}}^{-1}(\mathbf{x}-\mathbf{z})} \tag{12}$$

where $\bar{\mathbf{K}}$ is the covariance matrix. The covariance matrix is defined as follows.

$$\bar{K} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \ldots & \sigma_{1n}\\ \sigma_{21} & \sigma_{22} & \ldots & \sigma_{2n}\\ . & . & . & .\\ . & . & . & .\\ \sigma_{n1} & \sigma_{n2} & \ldots & \sigma_{nn} \end{bmatrix} \tag{13}$$

The three spectral components corresponding I_1, I_2, and I_3 planes are assumed to be decorrelated and further the variance of I_1, I_2, and I_3 component is assumed to be same, that is σ^2. Therefore, the covariance matrix can be expressed as,

$$\bar{K} = \begin{bmatrix} \sigma^2 & 0 & 0\\ 0 & \sigma^2 & 0\\ 0 & 0 & \sigma^2 \end{bmatrix} \tag{14}$$

Hence, substituting (14) in (12) we obtain,

$$P(W=x-z|Z,\theta)=\frac{1}{\sqrt{(2\pi)^3}\sigma^3}e^{-\frac{1}{2\sigma^2}\|\mathbf{x}-\mathbf{z}\|^2} \tag{15}$$

$P(Z = z) = \frac{1}{Z'}exp^{\frac{-U(z,\hat{\theta})}{T}}$ where $U(z, \hat{\theta})$ is the energy function corresponding to the a priori model of the label process. We assume that there are two types of interaction that contribute to the clique potential function. The first one is the intra-color-plane interaction and the second one is the inter-color-plane interaction process. They can be described as follows. Intra-color-plane process is described as $\sum_{c\in C_{in}} V_c(z^{(1)}, z^{(2)}, z^{(3)})$ and the inter-color-plane potential function is described as $\sum_{c\in C_{ir}} V_c(n^{(1)}, n^{(2)}, n^{(3)})$, where C_{in} and C_{ir} are total the number of cliques in intra-color-plane and inter-color-plane clique potential function respectively. $V_c(n)$ for two color components(for example I_1 and I_2) can be expressed as $V_c(n^1) = \alpha\{(n^{I_2}_{i',j'} - n^{I_1}_{i-1,j})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i,j-1})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i,j+1})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i+1,j})^2\}$. Substituting (15) and the prior distribution $P(Z = z)$ in (10) we obtain

$$(\hat{z}, \hat{n}) = \underset{(z,n)}{arg\,max} \; \frac{1}{\sqrt{(2\pi)^3}\sigma^3} e^{-\{\sum_{i=1}^{3} \frac{\|(x^{(i)} - z^{(i)}\|^2}{2\sigma^2} + \sum_{c\in C_{in}} V_c(z^{(1)}, z^{(2)}, z^{(3)}) + \sum_{c\in C_{ir}} V_c(n^{(1)}, n^{(2)}, n^{(3)})\}} \quad (16)$$

In (16), $\hat{n}$ denotes the estimated labels in the previous time step, and hence the minimization of (16) with respect to z and n reduces to minimizing (16) with respect to z only. Hence, this minimization can be expressed as,

$$\hat{z} = \underset{z}{arg\,min} \; \{\sum_{i=1}^{3} \frac{(x^{(i)} - z^{(i)})^2}{2\sigma^2} + \sum_{c\in C_{in}} V_c(z^{(1)}, z^{(2)}, z^{(3)}) + \sum_{c\in C_{ir}} V_c(n^{(1)}, n^{(2)}, n^{(3)})\} \quad (17)$$

Solving (17) yields the MAP estimates of the image labels and hence segmentation. The color image has three spectral components x^i, z^i, i=1,2,3, V_c is the clique potential function for all the three spectral components and C_{in} and C_{ir} is the set of all the cliques for intra-color-plane and inter-color-plane process respectively. In particular, we consider the following energy function

$$U(z, h, v) = \sum_{i,j} \alpha \left[\| z_{i,j} - z_{i,j-1} \|^2 (1 - v_{i,j}) + \| z_{i,j} - z_{i-1,j} \|^2 (1 - h_{i,j})\right] + \beta \left[v_{i,j} + h_{i,j}\right] + \sum_{c\in C_{ir}} V_c(n^{(1)}, n^{(2)}, n^{(3)}) \quad (18)$$

where, $[\alpha, \beta]^T$ is the set of unknown parameter vector that are selected on *ad hoc* basis, $V_c(n^1) = \alpha\{(n^{I_2}_{i',j'} - n^{I_1}_{i-1,j})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i,j-1})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i,j+1})^2 + (n^{I_2}_{i',j'} - n^{I_1}_{i+1,j})^2\}$ and $\| z_{i,j} \|^2 = \left(z^1_{i,j}\right)^2 + \left(z^2_{i,j}\right)^2 + \left(z^3_{i,j}\right)^2$. The vertical line field $v_{i,j} = 1$ if, $f_v(z_{i,j}, z_{i,j-1}) > thresh$, where $f_v(z_{i,j}, z_{i,j-1}) = \frac{1}{3}\sum_{q=1}^{3} | z^q_{i,j} - z^q_{i,j-1} |$ and the horizontal line field $h_{i,j} = 1$ if, $f_h(z_{i,j}, z_{i-1,j}) > thresh$, where $f_h(z_{i,j}, z_{i-1,j}) = \frac{1}{3}\sum_{q=1}^{3} | z^q_{i,j} - z^q_{i-1,j} |$. The posterior energy function can be expressed as follows

$$U_p(z, h, v) = \frac{\sum_{i=1}^{3}(x^i - z^i)^2}{2\sigma^2} + U(z, h, v) \quad (19)$$

The proposed hybrid algorithm and the SA are used to obtain the MAP estimate of equation (19).

A. Hybrid Algorithm

It is observed that SA algorithm takes substantial amount of time to converge to the global optimum solution. SA algorithm has the attribute of coming out of the local minima and converging to the global optimal solution. This feature could be attributed to the acceptance criterion(acceptance with a probability). We have exploited this feature, that is the proposed hybrid algorithm uses the notion of acceptance criterion to come out of the local minima and to be near the global optimal solution. Thus, in the hybrid algorithm, SA algorithm produces an intermediate solution that can be local to the optimal solution. In order to obtain the optimal solution, a local convergence based strategy is adopted for quick convergence. Towards this end, we have used Iterated Conditional Mode (ICM) [13] algorithm as the locally convergent algorithm. Thus, the proposed algorithm is a hybrid of both SA algorithm and ICM algorithm. The hybrid algorithm's working principle is as follows. Initially, a specific number of time steps of SA algorithm, fixed by trial and error, are executed to achieve the near optimal solution. Thereafter, ICM is run to converge to the desired optimal solution. This avoids the undesirable time taken by SA algorithm when the solution is close to the optimal solution. The steps of proposed hybrid algorithm are enumerated as below :

1) Initialize the temperature T_{in}.
2) Compute the energy U of the configuration.
3) Perturb the system slightly with suitable Gaussian disturbance.
4) Compute the new energy U' of the perturbed system and evaluate the change in energy $\Delta U = U' - U$.
5) If $(\Delta U < 0)$, accept the perturbed system as the new configuration Else accept the perturbed system as the new configuration with a probability $exp(-\Delta U)/t$ (where t is the temperature of cooling schedule).
6) Decrease the temperature according to the cooling schedule.
7) Repeat steps 2-7 till some prespecified number of epochs.
8) Compute the energy U of the configuration.
9) Perturb the system slightly with suitable Gaussian disturbance.
10) Compute the new energy U' of the perturbed system and evaluate the change in energy $\Delta U = U' - U$.
11) If $(\Delta U < 0)$, accept the perturbed system as the new configuration, otherwise retain the original configuration.
12) Repeat steps 8-12, till the stopping criterion is met. The stopping criterion is the energy $(U < threshold)$.

IV. Simulation

We have considered two, four and five class images having texture as well as scenes. Fig. 3(a) shows a five class color images and the corresponding ground truth image is shown in Fig. 3(b). Fig.3(c) shows the segmentation results obtained using only MRF model without interplane interactions. The model could not yield proper segmentation and pixel misclassification error as high as 25.78 percentage. The model parameters chosen are give in Table.1. We have incorporated the interplane interactions and called as DMRF model. The DMRF model when applied yields the results as shown in Fig. 3(d) The percentage of misclassification error reduced to 18.23 percentage. It is also observed that there are quite a bit of misclassification pixels. The model parameters of DCMRF model that uses constrained model in the intra plane only. Observed from Fig. 3(e), there are a few of misclassification pixels at the left top corner of the image and hence the percentage of misclassification is 3.63. Fig. 3(f) shows the results obtained by DCCMRF model. Except a few misclassified pixels there is proper segmentation. The model parameters for DCCMRF are also given in Table.1. Fig. 3(g) and (h) corresponds to DGMRF and JSEG method. From Fig. 3(g) it is clear that there are more misclassified pixels and the misclassification error is 19.64 percentage and for JSEG method the misclassification error is 2.9 percentage. Thus, it is found that the constrained model could model the texture effectively. Fig.2 shows the convergence of SA and hybrid algorithm. It is observed that hybrid algorithm converges at around 500 iteration where as SA converges at around 6000 iteration. Fig.4 shows an image with a hand,a ring and a textured background. This is a combination of texture and object. All the models MRF, DMRF, DCMRF, DCCMRF, DGMRF based method and JSEG method are tested and from Fig. 4 it is observed that DCCMRF yielded the best segmentation result. The percentage of misclassification is 2.39 percentage, which is lowest among all the method. The model parameters are given in Table.1. Here also DCCMRF could yield segmentation result and hence could model scene as well as texture. Fig.5 is an example of a scene image. The model parameters and the percentage of misclassification error are given in Table. 1 and Table. 2. This is a 4 class problem. Here also DCCMRF yielded results with minimum misclassification error. Hence, DCCMRF could be the best model among all the models considered and has the unifying property of modelling texture as well as scene.

TABLE I

PARAMETERS FOR IMAGES OF DIFFERENT CLASSES

Images	Intraplane parameters			
	α	β	σ	λ
Fig.3	0.019	2.9	1.2	0.001
Fig.4	0.002	2.9	0.11	1.05
Fig.5	0.019	2.9	0.9	0.001

V. CONCLUSION

In this paper we have proposed two new models DCMRF and DCCMRF based on the notion of martingale sequence. We have used Ohta model where we have decorrelated among different planes and then used partial correlation among the planes. It was observed that two proposed models possesses the attribute to model texture as well as scene. This was evident by testing the models on images having different classes. The model parameters were selected on trial and error basis. Current work focuses on model parameters estimation and segmentation.

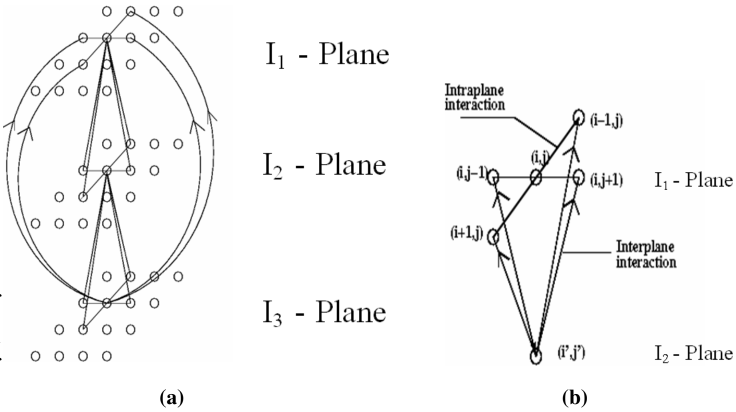

Fig. 1. (a) I_1, I_2, I_3 Plane Interaction (b) Interaction of one pixel of I_1-plane with I_2-plane

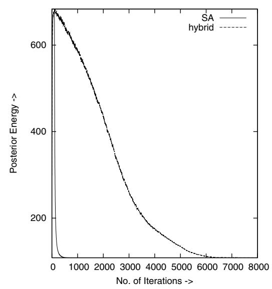

Fig. 2. Convergence of 'Texture-five-class' image using 'SA' and 'Hybrid' algorithm

REFERENCES

[1] H.D.Cheng,X.H.Jiang,Y.Sun,J.Wang,Color Image Segmentation: Advances and prospects. *Pattern Recognition*,vol.34,pp.2259-2281,2001.

[2] Y.I.Ohta,T.Kanade,T.Sakai,Color information for region segmentation. *Comp.Grap.Image.Process*,vol.62,pp.222-241,1980.

[3] S. Geman, D. Geman,Stochastic relaxation, Gibbs distributions,and the Bayesian restoration of images. *IEEE Transactions on Pattern Analysis And Machine Intelligence* vol. 6,pp. 721-741, 1984.

TABLE II

PERCENTAGE($\%age$) OF MISSCLASSIFICATION ERROR FOR DIFFERENT IMAGES

Images	MRF $Hybrid$	$DMRF$ $Hybrid$	$DCMRF$ $Hybrid$
Fig.3	25.78	18.23	3.63
Fig.4	10.65	6.91	3.08
Fig.5	17.48	16.98	12.26

Images	$DCCMRF$ $Hybrid$	$DGMRF$ $Hybrid$	$JSEG$
Fig.3	1.42	19.64	2.9
Fig.4	2.39	3.58	6.84
Fig.5	6.51	20.35	20.48

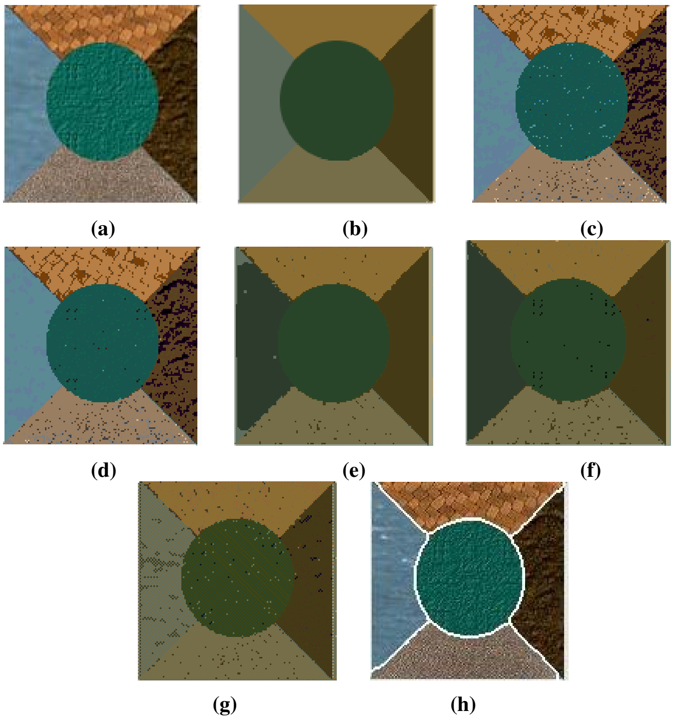

Fig. 3. (a)Five class texture image(128 x 128) (b)Ground Truth (c)MRF optimized using Hybrid (d)DMRF optimized using Hybrid (e)DCMRF optimized using Hybrid(f)DCCMRF optimized using Hybrid(g)DGMRF optimized using Hybrid(h)JSEG result

[4] S.A.Kirkpatrick and C.Gelatt Jr. and M Vecchi,Optimization by Simulated Annealing. *Science*,vol-220,pp-671-680,1983.

[5] Z.Kato,T.C.Pong,S.G.Qiang,Multicue MRF Image segmentation:Combining Texture and Color Features. *IEEE.comp.Society ICPR*,2002.

[6] P.K Nanda,MRF model learning and its application to image restoration and segmentation. *PhD dissertation, Electrical Engg. Department, I.I.T. Bombay*,1995.

[7] F.Destrempes,M.Max and A.J.Francois,A stochastic method for bayesian estimation of Hidden Markov Random Field models with application to a color model. *IEEE Transactions on Image Processing*,vol-14,pp-1096-1108,2005.

[8] Q.Xu,J.Yang,S.Ding,Color texture analysis using the wavelet-based hidden Markov model. *Pattern.Recog.Letter*.vol.26,pp.1710-1719,2005.

[9] Z.Kato.,T.C.Pong,A Markov random field image segmentation model for color textured images. *Image.vision.comp.*,vol.24,pp.1103-1114,2006.

[10] H.Permuter,J.Francos,I.Jermyn,A study of Gaussian mixture models of color and texture features for image classification and segmentation. *Pattern.Recog.*,vol.39,pp.695-706,2006.

[11] Y.Deng,B.S.Manjunath,Unsupervised Segmentation of Color-Texture Regions in Images and Video. *IEEE Transactions on Pattern Analysis And Machine Intelligence* vol. 23,pp. 800-810, 2001.

[12] S.Z.Li,*Markov Random Field modeling in computer vision* (Springer, Berlin, 1995).

[13] J.Besag,On the statistical analysis of dirty pictures. *J.Roy.Statistical Soc.B* vol. 62,pp. 259-302, 1986.

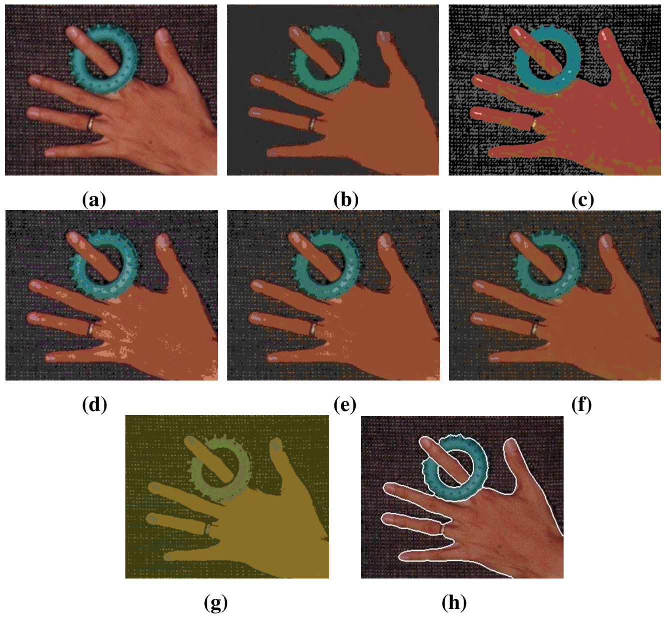

Fig. 4. (a)Hand Ring image(303 x 243)(b)Ground Truth (c)MRF optimized using Hybrid (d)DMRF optimized using Hybrid (e)DCMRF optimized using Hybrid(f)DCCMRF optimized using Hybrid(g)DGMRF optimized using Hybrid(h)JSEG result

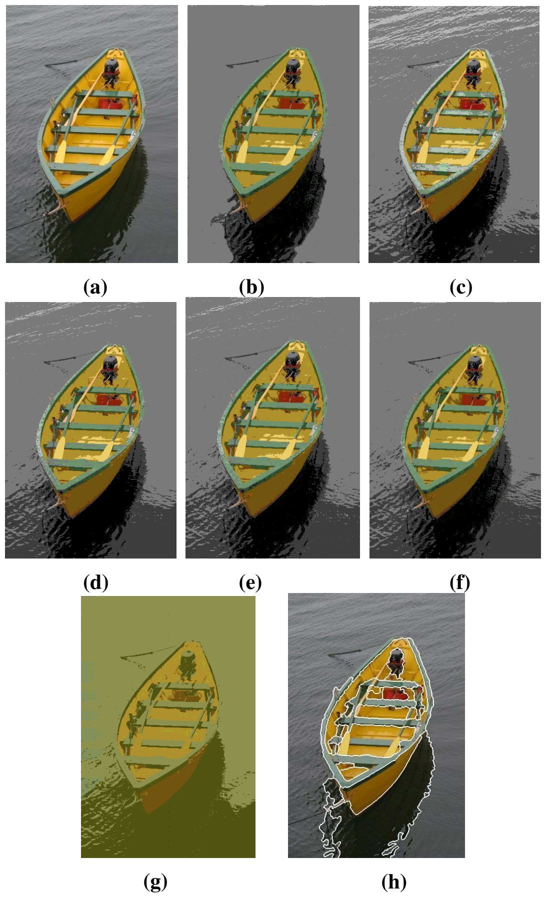

Fig. 5. (a)Water-Boat image(348 x 522) (b)Ground Truth (c)MRF optimized using Hybrid (d)DMRF optimized using Hybrid (e)DCMRF optimized using Hybrid(f)DCCMRF optimized using Hybrid(g)DGMRF optimized using Hybrid(h)JSEG result