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Unsupervised Color Image Segmentation using Compound Markov Random Field Model

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Abstract. In this paper, we propose an unsupervised color image segmentation scheme using homotopy continuation method and Compound Markov Random Field (CMRF) model. The proposed scheme is recursive in nature where model parameter estimation and the image label estimation are alternated. Ohta (I_1, I_2, I_3) model is used as the color model for image segmentation and we propose a compound MRF model taking care of intra-color and inter-color plane interactions. The CMRF model parameters are estimated using Maximum Conditional Pseudo Likelihood (MCPL) criterion and the MCPL estimates are obtained using homotopy continuation method. The image label estimation is formulated using Maximum *a Posteriori* criterion and the MAP estimates are obtained using hybrid algorithm. In the context of misclassification error, the proposed unsupervised scheme with CMRF model exhibited improved segmentation accuracy as compared to MRF model and Kato's method.

Key words: Color Image,Color Model,Segmentation,Simulated Annealing and MRF model

1 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, and is very suitable for many image processing applications [2].

Stochastic models, particularly MRF models, have been successfully used as the image model for image restoration and segmentation [3],[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. The model parameters can be estimated in both supervised and unsupervised framework [5]. Homotopy continuation methods are globally convergent methods that have been used to trace the zeros of a function and hence determines the solution of functions [6],[7].

In this work, a Compound MRF model based color image segmentation scheme is proposed in unsupervised framework. We have used Ohta(I_1, I_2, I_3) color space to model the color images. In the proposed scheme, the compound MRF model parameters and the image labels are estimated concurrently. Since the image label estimates and the estimates of model parameters are dependent on each other, obtaining global estimates of label as well as model parameters is very hard. Hence, we have proposed a recursive scheme for estimation of image labels and model parameters. The recursive scheme yields partial optimal solutions as opposed to optimal solutions. The MRF model parameter estimation problem is formulated in Maximum Conditional Pseudo Likelihood (MCPL) framework and the MCPL estimates are obtained using homotopy continuation bases algorithm. The image label estimation problem is formulated in Maximum a Posteriori (MAP) framework and the MAP estimates are obtained using the proposed hybrid algorithm. The proposed unsupervised algorithm, has been successfully tested on different images, however, for the sake of illustration we have presented two results and a comparison is made with the Kato *et al* [5] method.

2 Compound MRF Model

MRF modeling for color is more complex than the gray image modeling in the sense that it has to take care of the different color components of a color space. In this work, we have employed (Ohta(I_1, I_2, I_3)) color model. MRF model is used to model images in both RGB and Ohta color space. The proposed compound MRF model is based on the following notion: (i)Intra-color-plane (I_1 or I_2 or I_3) enities of each color plane are modeled as MRF model (ii)Inter-color-plane interactions among color planes for e.g.(I_1 and I_2 and I_3), are also modeled as MRF. This process of interaction(intra-plane and inter-plane) is shown in Fig. 1(a) and Fig. 1(b).

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. 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

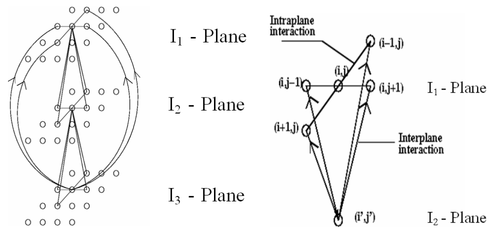

Fig. 1. (a) I_1, I_2, I_3 Plane Interaction (b) Interaction of one pixel of I_1-plane with I_2-plane

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). Thus the energy function, $U(z,\theta) = \sum_{c \in C_{in}} V_c(z^{(1)}, z^{(2)}, z^{(3)}) + \sum_{c \in C_{ir}} V_c(n^{(1)}, n^{(2)}, n^{(3)})$, where $V_c(z^{(1)}, z^{(2)}, z^{(3)})$ correspond to the intra-color-plane pixels and $V_c(n^{(1)}, n^{(2)}, n^{(3)})$ correspond to the inter-color-plane pixels.

3 Unsupervised Image Segmentation

In unsupervised segmentation scheme, the labels are the MAP estimates assuming the estimates of the associated model parameter $\hat{\theta}$ are available. In this scheme, the MAP estimates of the labels and the estimates of the model parameters need to be carried out concurrently. Thus, an estimation strategy needs to be developed, which using the observed image, X,will yield an optimal pair (Z^{opt}, θ^{opt}). The following joint optimality criterion is considered,

$$(Z^{opt}, \theta^{opt}) = arg \quad \max_{z,\theta} P(Z = z|X = x, \theta) \tag{1}$$

The estimated pair (Z^{opt}, θ^{opt}) satisfying (1) are the global optima of $P(Z = z/X = x, \theta)$ with respect to Z and θ. Since both the entities Z and θ are unknown and interdependent, the problem is a very hard problem. Therefore, it is necessary to opt for strategies for suboptimal solution. In (1), z, θ could be viewed as a set of parameter of the given function $P(Z = z/X = x, \theta)$. For such kind of problems in deterministic framework, Wendell and Horter[8] have proposed an alternate approach that would yield suboptimal solutions instead of optimal solution. Their approach is based on splitting the variables followed by recursively estimating the parameters. They have proved that, the final estimate in this process is called as the partial optimal solution. In our case, in stochastic framework, we in the same spirit, venture to split the original problem into estimation of labels(z) and parameters θ to obtain the partial optimal solutions The splitting of the variables can be expressed as follows

$$(Z^*) = arg \quad \max_{z} P(Z = z|X = x, \theta^*) \tag{2}$$

$$(\theta^*) = arg \max_{\theta} P(Z = z^*|X = x, \theta) \tag{3}$$

These partial optimal solutions Z^* and θ^* are not global maxima, rather they are almost always local optimal solutions [8]. But with $\theta = \theta^*$, the estimate z^* is global optimal satisfying equation (2) and analogously for $z = z^*$, θ^* is global optimal satisfying equation(3). Since neither θ^* nor z^* is known, evaluating Z^* and θ^* is also hard and hence, a recursive scheme is adopted where the model parameter estimation and segmentation is alternated. Let at the k^{th} iteration $\theta^k = [\alpha^k, \beta^k]^T$ be the estimate of model parameters and z^k be the estimate of the labels of the observed image. We adopt the following recursion

$$(Z^{k+1}) = arg \max_{z} P(Z = z|X = x, \theta^k) \tag{4}$$

$$(\theta^{k+1}) = arg \max_{\theta} P(Z = z^{k+1}|X = x, \theta) \tag{5}$$

The first problem of equation (4) is solved using Bayesian approach [3]. The optimal value of θ^k is obtained by the proposed Homotopy Continuation method. The MAP estimates are obtained by the proposed hybrid algorithm. One estimate of z^k and θ^k constitute *one combined iteration.* This recursion is continued for finite number of steps to obtain z^* and θ^*. Thus, the partial optimal solutions are obtained. The model parameter θ has been estimated using Homotopy Continuation method proposed by Panda *et al* [9]. In the following we briefly explain the estimation of image label.

4 Image Label Estimation

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,

$$(\hat{z}) = \underset{z}{arg\, max}\, P(Z = z|X = x, \hat{\theta}) \tag{6}$$

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

After carrying out simplification, the problem reduces to the following minimization problem,

$$\hat{z} = \underset{z}{arg\, min} \{\sum_{i=1}^{3} \frac{(x^{(i)} - z^{(i)})^2}{2\sigma^2} + \sum_{c \in C_{in}} V_c(z^{(1)}, z^{(2)}, z^{(3)}) + \sum_{c \in C_{ir}} V_c(n^{(1)}, n^{(2)}, n^{(3)})\} \tag{7}$$

where $V_c(z^{(1)}, z^{(2)}, z^{(3)})$ and $V_c(n^{(1)}, n^{(2)}, n^{(3)})$ corresponds to the clique potential function of intra-color-plane pixels and inter-color-plane pixels respectively. In this work, we have considered Weak Membrane MRF model of Geman and Geman with line field [3]. The MAP estimates of the image labels $\hat{z}$ are obtained using the Hybrid algorithm. The algorithm is a combination of Simulated Annealing (SA) and Iterated Conditional Mode (ICM) algorithm. SA is run till the energy reaches a threshold and thereafter ICM is run to obtain the MAP estimates of labels.

5 Simulation

One outdoor images and one indoor image are considered in simulation. The first original image, an indoor image with three objects on a table, is shown in Fig.2(a). In order to compute the percentage of misclassification error, the Ground Truth image, as shown in Fig.2(b), is constructed manually. The estimated MRF model parameters are, $\alpha = 0.1025$, $\beta = 2.28$ and $\sigma = 0.5$. However σ is chosen by trial and error and is fixed at 0.5. The results obtained by basic MRF model is shown in Fig.2(c), where it is observed that some portions of the stapler are not prominent. CMRF model based approach could prominently preserve these portions. In Fig.2(d) it is observed that the edges and the shapes could be recovered. Observing the result obtained by Kato's method, as shown in Fig.2(e), the edges are dithered and some portion of the stapler has been misclassified. However, the percentage of misclassification error in case of MRF model is 6.5% which is close to that of CMRF model i.e. 2.91%. The observations are different in case of real outdoor images. Fig.3(a) shows an image with leaves and water body and the corresponding ground truth is shown in Fig.3(b). The misclassification error for MRF model is 9.2% which is higher than that of CMRF model which is 3.5%. The estimated MRF model parameters are $\alpha = 0.003$, $\beta = 8.98$ and $\sigma = 0.35$. Thus, the scheme with CMRF model yielded satisfactory results for indoor as well as outdoor scenes.

6 Conclusion

An unsupervised color image segmentation scheme is proposed with homotopy continuation method and CMRF model. Because of the globally convergent property of the homotopy continuation method, the algorithm can start from a arbitrary set of model parameters and converges to the partial optimal sets. In order to speed up the MAP estimation process, hybrid algorithm is used. The only limitation of the scheme is to choose a proper value of σ for the degradation process. However, estimation of σ together with the model parameters is currently focused.

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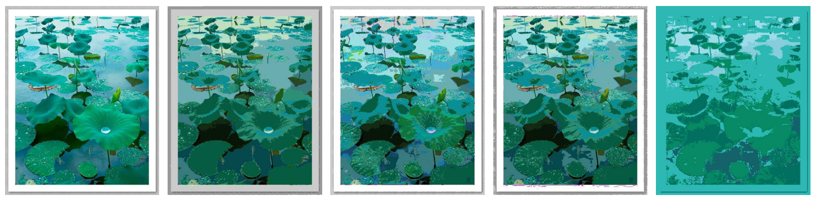
(a) (b) (c) (d) (e)

Fig. 2. (a)*Stapler(Indoor) image(128 x 128)* (b)Ground Truth (c)MRF optimized using Hybrid (d)CMRF optimized using Hybrid (e)MRF_KATO



(a) (b) (c) (d) (e)

Fig. 3. (a)*Leaves-Water image(512 x 627)* (b)Ground Truth (c)MRF optimized using Hybrid (d)CMRF optimized using Hybrid (e)MRF_KATO

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