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Multiresolution Approach for Color Image Segmentation using MRF Model

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ABSTRACT

In this paper, the color image segmentation problem is addressed in supervised framework. In the supervised framework, we assume to have one original image from the class of images from which the given image is derived. In this framework, We have used Markov Random Field(**MRF**) to model the image label process and the MRF model parameters are estimated using the conditional pseudolikelihood criterion. Ohta(I_1, I_2, I_3)model is used as the color model. The segmentation problem is formulated as the pixel labeling problem. The image model parameter estimation problem is formulated using pseudo-likelihood criterion. The image label estimation problem is cast in Maximum {*a Posteriori*} (MAP) framework. These MAP estimates are obtained using the proposed new hybrid algorithm and compared with Simulated Annealing (SA) algorithm. It is observed that the proposed hybrid algorithm converge much faster than that of SA. The segmentation scheme is further improved by adhering to multiresolution approach where the segmentation is carried at a coarse level and reconstructed to a finer level. The proposed scheme appears to be more viable from a practical standpoint.

Index Terms— *Ohta color Space, MAP Estimate, Segmentation, Simulated Annealing (SA), Hybrid Algorithm*

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 [2]. A color model is used to represent various colors in 3-D coordinate system. Different color models such as RGB, HSV, YIQ, (I1, I_2, I_3), CIE XYZ, CIE Luv,CIE Lab are used to represent different colors [2]. From the reported study, HSV and (I1, I_2, I_3) have been extensively used for 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 [13].

Besides color model, image model also plays an important role in image segmentation. Stochastic models, particularly Markov Random Field (MRF) model, has been extensively used as the image model while addressing the problem of image restoration and segmentation [5,11]. Often, the image segmentation problem is cast using a maximum a posteriori (MAP) criterion and the MAP estimates are obtained by simulated annealing (SA) algorithm [8]. 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 [7, 10, 12, 6, 9, 11]. Recently color image is segmented in unsupervised framework [4] using Hidden Markov Random Field (HMRF) model as the image model. Even though substantial work has been done and satisfactory results have been reported, there are still challenges to obtain segmentation in the context of real-time.

We have addressed the color image segmentation problem in a supervised framework. The term supervised is usually used when both image model parameters as well as the image labels are known a priori. The problem is formulated as a pixel labeling problem. True labels of the given image are modeled as the MRF model. Image segmentation is achieved with the help of maximum a posteriori (MAP) estimation combining with MRF model. We have assumed to have an known original image from a class of images from which the given observed image is derived. The observed image is assumed to be the degraded version of the unknown segmented image. This unknown segmented image is modeled as MRF model, and the degradation process is assumed to be Gaussian. I_1, I_2, I_3 is used as the color model. The associated image model parameters need to be estimated and hence, the MRF model parameter estimation problem is formulated using the notion of pseudo-likelihood criterion. With known MRF model parameters, the image segmentation problem is formulated as a pixel-labeling problem. The pixel labels are estimated using the Maximum a Posteriori (MAP) criterion. Often, these MAP estimates of the image labels are obtained using Simulated Annealing (SA) algorithm. It is observed that SA takes appreciable amount of time to obtain the MAP estimates. In order to obtain these MAP estimate, we have proposed a hybrid algorithm exploiting the notions of local and global search. Upon comparison of SA and the hybrid algorithm, it is found that the hybrid algorithm is much faster than that of SA. In order to make this scheme viable from a practical standpoint, Gaussian pyramid [1] multiresolution approach is adopted. The image model parameters are estimated for the image at a coarse resolution and the segmented image is obtained at the same resolution. The segmented image at the finest resolution is obtained by reconstructing from the segmented image at coarse resolution. This scheme could be perceived to be implemented in real time. Examples are presented to validate our approach.

2. PROBLEM STATEMENT

We assume all the images to be defined on a discrete rectangular lattice L=N x N. Let Z denote the label process associated with the true labels of the segmented image. In case of color images, $Z=[Z^1, Z^2, Z^3]^T$ denote the three components of some color coordinate system, for example Z1 could correspond to red, Z2 to green and Z3 to blue in the RGB color coordinate system. The label process, Z is assumed to be Markov Random Field with respect to a neighbourhood system η and is described by in terms of its local characteristics [5].

$$P(Z_{i,j}=z_{i,j} \mid Z_{k,l}=z_{k,l}, k,l \in N \times N, (k,l) \neq (i,j)) = P(Z_{i,j}=z_{i,j} \mid Z_{k,l}=z_{k,l}, (k,l) \in \eta)$$

Here Z is an MRF or equivalently Gibb's distributed (GD) which is considered as a priori distribution. This is expressed as $P(Z=z|\phi)=\frac{1}{Z'}e^{-U(x,\phi)}$ where $Z'=\sum_x e^{-U(x,\phi)}$ is the partition function, ϕ represents the clique parameter vector, the exponent term $U(Z,\phi)$ is called the energy function and is of the form $U(Z,\phi)=\sum_{C:(i,j)\in c} V_c(z,\phi)$, is a sum of clique potentials $V_c(z,\phi)$ over all possible cliques C, ϕ is the set of clique parameters, and z is a realization of Z. Generally the parameter vector $\theta=[\phi^T, \sigma^2]$ is unknown and need to be estimated. The given color image X is assumed to be the degraded version of the label process and thus the degradation model is given as

$$X_{i,j} = Z_{i,j} + W_{i,j}, \ \forall (i,j) \in (N \, x \, N) \qquad (1)$$

Where X denotes the random field associated with the degraded image and Z denotes the label process, W denotes the Gaussian process. Each pixel $Z^q{}_{i,j}$ $(q=1,2,3)$ takes a value from a finite set $G^q \in [0,255]$.

We make the following assumptions: (a) $W_{i,j}{}^p$ $for\, 1 \leq p \leq 3$ is a white Gaussian sequence with zero mean variance σ^2. (b) $W_{i,j}{}^p$ is statistically independent of $Z_{k,l}$, for all (i, j) and (k, l) belonging to N x N, where $1 \leq p,q \leq 3$.

In this supervised scheme, we assume to estimate the image model parameter vector ϕ before estimation of image labels. The variance σ^2 of the Gaussian process is selected on an ad-hoc basis. Since, the parameter vector θ is estimated a priori, the image labels need to be estimated.

Let $\hat{z}$ be the realization of the segmented image corresponding to the label process Z. This is cast in MAP framework and the following optimality criterion is adopted

$$\hat{z} = \arg\max_z P(Z=z \mid X=x, \theta) \qquad (2)$$

Where $\hat{\theta}=[\hat{\phi}^T, \sigma^2]^T$ and $\phi=[\alpha,\beta]^T$, α,β are the MRF model parameters. The MAP estimate is obtained by the proposed hybrid algorithm and SA. In this supervised scheme, we assume to have an image belonging to the image class from which the given image is derived. The model parameters of the assumed known image are estimated and are used for the given image. This estimation problem is formulated using MCPL framework. The optimality criterion considered is

$$\hat{\theta} = \arg\max_\theta P(Z=z/\theta) \qquad (3)$$

Having determined $\hat{\theta}$, we use the MAP estimation problem for estimating the image labels and hence segmentation.

3. MAP ESTIMATION OF IMAGE LABELS

The labeling $\hat{z}$ is obtained by maximizing the posterior probability $P(Z=z \mid X=x,\theta)$. Hence, the optimality criterion is

$$\hat{z} = \arg\max_{z} P(Z = z \mid X = x, \hat{\theta}) \qquad (4)$$

Since z is unknown the above can not be computed. So, by using Baye's theorem , equation (4) can be expressed as

$$\hat{z} = \arg\max_{z} \frac{P(X = x \mid Z = z, \theta) P(Z = z)}{P(X = x \mid \theta)} \qquad (5)$$

Since X corresponds to the given image $P(X = x|\theta)$ is constant. $P(Z = z)$ is the a priori probability of the labels. According to Hammersley-Clifford theorem

$$P(Z = z) = \frac{1}{Z'} e^{-U(z)/T} \qquad (6)$$

Where, Z' = normalizing constant or partition function and T = temperature which controls the sharpness of the distribution. Usually T is taken as 1. The only unknown remaining in (5) is the $P(X = x|Z = z, \theta)$. Here we assume that the observed image can be considered as a transformed and degraded version of an MRF realization. Using the degradation image model of (1), $P(X = x|Z = z, \theta)$ can be written as

$$\begin{aligned} P(X = x \mid Z = z, \theta) &= P(X = z + w \mid Z, \theta) \\ &= P(W = x - z \mid Z, \theta) \end{aligned} \qquad (7)$$

Since W is a Gaussian process and using the assumption stated in section 3 we obtain

$$P(W = x - z \mid Z, \theta) = \frac{1}{\sqrt{(2\pi)^n \det[\overline{K}]}} e^{-\frac{1}{2}(x-z)^T \overline{K}^{-1}(x-z)} \qquad (8)$$

Where $\overline{K}$ is the covariance matrix. There are three spectral components present in a color image and we have assumed that the components are uncorrelated in Ohta color space having the same variance. Hence equation (8) reduces to

$$P(W = x - z \mid Z, \theta) = \frac{1}{\sqrt{(2\pi)^3}\sigma^3} e^{-\frac{1}{2\sigma^2}(x-z)^2} \qquad (9)$$

Substituting (9) and (6) in (5) we have

$$\hat{z} = \arg\max_{z} \frac{1}{Z'\sqrt{(2\pi)^3}\sigma^3} e^{-\left[\frac{(X-Z)^2}{2\sigma^2} + U(z,\phi)\right]} \qquad (10)$$

The maximization of the above function is equal to the minimization of the following.

$$\hat{z} = \arg\min_{z} \left[\frac{(X-Z)^2}{2\sigma^2} + U(z,\phi)\right] \qquad (11)$$

As color image has three spectral components, (11) can be represented as

$$\hat{z} = \arg\min_{z} \left[\frac{(x^{(1)} - z^{(1)})^2 + (x^{(2)} - z^2)^2 + (x^{(3)} - z^{(3)})^2}{2\sigma^2} + \sum_{c \in C} V_c(z^{(1)}, z^{(2)}, z^{(3)})\right] \qquad (12)$$

Where V_c is the clique potential function for all the three components, C is the set of all cliques and 1, 2 and 3 indicate the three spectral components. In particular we consider the energy function

$$\begin{aligned} U(z,h,v) = \sum_{i,j} \alpha [\| z_{i,j} - z_{i,j-1} \|^2 (1 - v_{i,j}) + \\ \| z_{i,j} - z_{i-1,j} \|^2 (1 - h_{i,j})] + \beta [v_{i,j} + h_{i,j}] \end{aligned} \qquad (13)$$

(7)

Where $\|z_{i,j}\|^2 = (z^1{}_{i,j})^2 + (z^2{}_{i,j})^2 + (z^3{}_{i,j})^2$.

The vertical line field v_{ij} = 1 if $f_v(z_{ij}, z_{i,j-1})$ > thresh and the horizontal line field h_{ij} = 1 if $f_h(z_{ij}, z_{i,-1,j})$ > thresh . In our simulation work we use

(8)

$$f_v(z_{i,j}, z_{i,j-1}) = \frac{1}{3}\left|\sum_{q=1}^{3} z^q{}_{i,j} - z^q{}_{i,j-1}\right| \qquad (14)$$

$$f_h(z_{i,j}, z_{i-1,j}) = \frac{1}{3}\left|\sum_{q=1}^{3} z^q{}_{i,j} - z^q{}_{i-1,j}\right| \qquad (15)$$

This amounts to deciding the presence or absence of the line fields v_{ij} and h_{ij}, on the color coordinate $I_1 = (R + G + B)/3, I_2 = (R - B)/2$ *and* $I_3 = (2G - R - B)/4$

The posterior energy function will be

$$U_p(z,h,v) = U(z,h,v) + \frac{\frac{1}{3}\|x-z\|^2}{2\sigma^2} \quad (16)$$

$[\alpha, \beta]^T$ are unknown parameters that are to be estimated,

$$\|x-z\|^2 = \sum_{q=1}^{3}\sum_{i,j}(x^q{}_{i,j} - z^q{}_{i,j})^2 \quad (17)$$

If the parameters are known, segmentation is achieved by minimizing $U_p(z,h,v)$ with respect to z,h,v. The proposed hybrid algorithm and the SA are used to obtain the MAP estimate of equation (12).

4. MRF MODEL PARAMETER ESTIMATION

The MAP criterion needs the parameter vector ϕ to be estimated earlier. We estimate the model parameters making use of the given original image. Since, σ^2 is selected on ad-hoc basis, the model parameter vector ϕ need to be estimated. Therefore, the problem can be stated as the following

$$\hat{\phi} = \arg\max_{\phi} P(Z = z \mid \phi) \quad (18)$$

Since Z is a MRF, we have

$$\hat{\phi} = \arg\max_{\phi} \frac{\exp(-U(z,\phi))}{\sum_{\xi}\exp(-U(\xi,\phi))} \quad (19)$$

Where ξ ranges over all realizations of the image Z. Because of the denominator of computation of the joint probability $P(Z = z \mid \phi)$ is extremely difficult task. We maximize the pseudolikelihood function $\hat{P}(Z = z \mid \phi)$ instead of the likelihood function $P(Z = z \mid \phi)$ where,

$$\prod_{(i,j)\in L} P(Z_{i,j} = z_{i,j} \mid Z_{m,n} = z_{m,n}, (m,n) \neq (i,j), (m,n) \in \eta_{i,j}, \phi) \overset{\Delta}{=} \hat{P}(Z = z \mid \phi) \quad (20)$$

From the definition of marginal conditional probability, we can write

$$P(Z_{i,j} = z_{i,j} \mid Z_{k,l} = z_{k,l}, (k,l) \neq (i,j), \forall (i,j) \in (N \times N), \phi) = \frac{P(Z = z \mid \phi)}{\sum_{z_{i,j}\in M} P(Z = z \mid \phi)} \quad (21)$$

Because of MRF assumption,

$$P(Z_{i,j} = z_{i,j} \mid Z_{m,n} = z_{m,n}, (m,n) \neq (i,j), m,n \in \eta_{i,j}, \phi) = \frac{\exp(-\sum_{c\in C} V_c(z,\phi))}{\sum_{z_{i,j}\in M}\exp(-\sum_{c\in C} V_c(z,\phi))} \quad (22)$$

Substituting equation (22) in (20) we have

$$\hat{P}(Z = z \mid \phi) \approx \prod_{(i,j)\in L} \frac{\exp(-\sum_{c\in C} V_c(z,\phi))}{\sum_{z_{i,j}\in M}\exp(-\sum_{c\in C} V_c(z,\phi))} \quad (23)$$

Therefore, the maximization problem reduces to

$$\arg\max_{\phi} \hat{P}(Z = z \mid \phi) = \arg\max_{\phi} \prod_{(i,j)\in L} \frac{\exp(-\sum_{c\in C} V_c(z,\phi))}{\sum_{z_{(i,j)\in M}}\exp(-\sum_{c\in C} V_c(z,\phi))} \quad (24)$$

The summation is over all possible labels M and L = N x N denotes the size of the image. We carry out the maximization process and obtain the estimate of parameter vector ϕ with the help of homotopy continuation method based algorithm.

It is clear from above that the parameter estimation problem has been reduced to maximization of highly non-linear equation(24) with respect to ϕ. Towards this end let

$$f(\phi) = \frac{\partial}{\partial\phi}\{\log[\hat{P}(X = x^{k+1} \mid Y = y, \phi)]\} \quad (25)$$

Now the homotopy method [3] is employed to solve $f(\phi) = 0$. In the following, we develop a general framework for solving $f(\phi) = 0$ using homotopy continuation method where ϕ is the unknown parameter vector to be determined.

In the continuation method we need to trace the homotopy path from a solution of a known system to that of the desired solution. In this regard, we have considered the fixed point homotopy map [3] which offers the advantage of arbitrary starting point for the path. This fixed point map is given by

$$h(\phi, \lambda, q) = \lambda f(\phi) + (1-\lambda)(\phi - q) \quad (26)$$

Where $0 \le \lambda \le 1$ and q is an arbitrary starting point. Here the predictor-corrector method is employed to track the path defined by the homotopy.

For the fixed point homotopy map considered, the final update equation is as follows

$$\hat{\phi}^k = \phi^k - \Delta\phi^k \quad (27)$$

The intermediate steps for arriving the above equation is given in [11]. If $\hat{\phi}_0^{\,k}$ estimated is not on the path then it is taken as the initial point in the correction step. Otherwise $\hat{\phi}_0^{\,k}$ is considered as the next point on the path. Suppose $|\hat{\phi}^k{}_{M+!} - \hat{\phi}^k{}_M| \le \gamma$ then we set $\hat{\phi}^k{}_M = \hat{\phi}^k = \phi^{k+1}$.

5. PROPOSED HYBRID ALGORITHM

It is observed that SA algorithm takes substantial amount of time for convergence. This algorithm also helps to come out of the local minima and converge to the global optimal solution. This feature could be attributed to the acceptance criterion (acceptance with a probability). We have exploited this feature, which is the proposed hybrid algorithm uses the notion of acceptance criterion to come out of the local minima. Subsequently, it is assumed that solution is locally available and hence local convergence based strategy is adopted for quick convergence. A specific number of iterations are executed to achieve the near optimal solution. This number of iteration is fixed by trial and error. This avoids the undesirable time taken by SA, while 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 the energy *ΔU = U – U'*.
5. If *(ΔU< 0)*, accept the perturbed system as the new configuration.

Else accept the perturbed system as the new configuration with a probability exp *(-ΔU/KT)* (where t is the temperature of cooling schedule).

6. Decrease the temperature according to the cooling schedule.
7. Repeat steps 2-7 till the temperature decreases to sufficiently low value
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 the energy *ΔU = U – U'*.
11. If *(ΔU< 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 $(U < threshold)$

6. RESULTS AND DISCUSSION

Different real images have been considered in simulation. The *a posteriori* energy function as given by (29) is considered in simulation. This is reproduced here for ease of reference

$$U_p(z,h,v) = U(z,h,v) + \frac{\frac{1}{3}\|x-z\|^2}{2\sigma^2} \quad (28)$$

where

$$U(z,h,v) = \sum_{i,j} \alpha[\|z_{i,j} - z_{i,j-1}\|^2 (1-v_{i,j}) + \|z_{i,j} - z_{i-1,j}\|^2 (1-h_{i,j}) + \beta[v_{i,j} + h_{i,j}] \quad (29)$$

The *a priori* image model parameters α and β are estimated by the proposed homotopy continuation method mentioned in section 5.

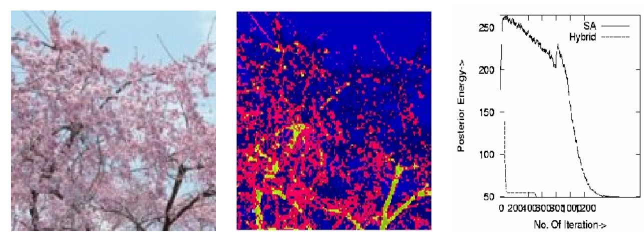
The first image considered is shown in Fig. (1) and the estimated model parameters are α = 0.031 and β = 4.1. Segmentation result obtained by Hybrid algorithm is shown in Fig. 1(b) and convergence of both the algorithm is shown in Fig. 1(c). For the second image the parameters are α = 0.02 and β = 4.5. For third image the estimated parameters are α = 0.02 and β = 4.1. For the "House" image shown in Fig. (4), the estimated model parameters are α = 0.116 and β = 2.93. For the "Checker-board" image shown in Fig. (5) the model parameters are α = 0.064 and β = 4.2. The observed image model is given by equation (1) where the observed image is assumed to be the degraded version of the true labels. The MAP estimate of the labels are obtained by the hybrid algorithm and also Simulated Annealing (SA) algorithm. The segmentation result of figure (5) is shown in Fig.5 (b) and the convergence of both the algorithms is shown in Fig.5(c). It is found from Fig.5(c) that SA takes around 3000 iterations to converge while the proposed hybrid algorithm converges at around 200 iterations. The noise variance σ is selected on an ad-hoc basis. Similar observations are also made for images shown in Fig. (6) and Fig. (7).

The proposed hybrid algorithm is found to converge faster than that of SA. The estimated parameters used for Fig. (6) and Fig. (7) are α = 0.042 and β = 4.1 and α = 0.04 and β = 4.17 respectively. The above two estimated model parameters imply the images of Fig. (6) and Fig. (7) belonging to the same class. Hence, any one set of the parameters can be used for the two images. We have used α = 0.042 and β = 4.1.

For real time implementation, the only bottleneck is the time taken by the SA algorithm to obtain the MAP estimate of labels. In order to reduce the computational burden, multiresolution approach is adopted. Images at different resolution are generated by Gaussian pyramid [1]. The program is run on Intel P-IV, 1.9GHZ, 128MB RAM machine and the time taken by the hybrid algorithm with and without multiresolution is tabulated in Table.1. In the multiresolution approach the parameter estimation and the image label estimation is carried out at (128x128) for Fig. (8) and (64x64) for Fig.(9) and Fig.(10). The segmented result of coarse resolution is reconstructed to the finest resolution. These reconstructed results at the finest resolution are shown in Figures 8, 9 and 10. It may be observed from Fig.9 (b) that the segmented image does not preserve the sharpness of the edges. This could be attributed to the fact that the edges are filtered while obtaining the coarse image using the Gaussian pyramid. This is reflected in the segmented image at coarse resolution and also in the finest resolution. We can get similar observation from Fig.10 (b). It is observed from Table.1 that hybrid algorithm in multiresolution approach takes 17sec for (128 x 128) image. Similar observations are also made for Fig.6 and Fig.7. As observed from Table.2 and Table.3, time taken by hybrid algorithm is 7sec. and 3sec respectively thus making it viable for real time implementation.

(a) (b) (c)

Figure 1. (a) Original "Rock" image of size (150x150) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm

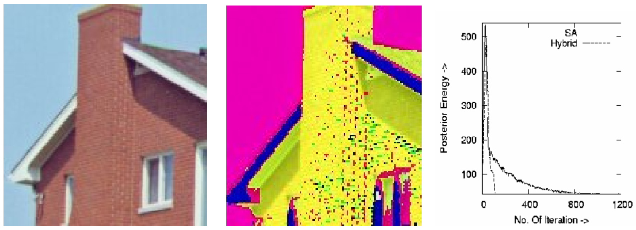


(a) (b) (c)

Figure 2. (a) Original "Tree with Leaves" image of size (150x150) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm

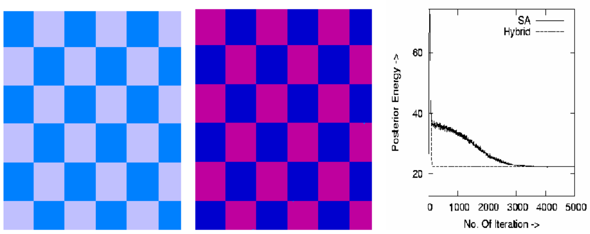
(a) (b) (c)

Figure 3. (a) Original "Indoor" image of size (120x120) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm



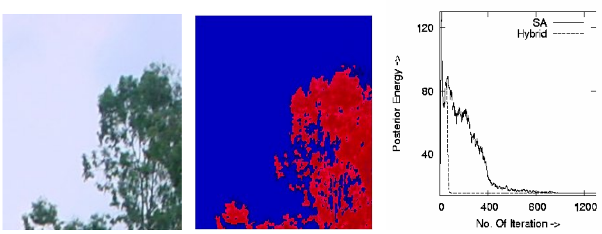
(a) (b) (c)

Figure 4. (a) Original “House” image of size (128x128) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm



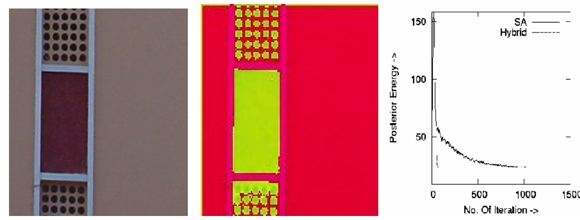
(a) (b) (c)

Figure 5. (a) Original “Checker-Board” image of size (256x256) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm



(a) (b) (c)

Figure 6. (a) Original “Tree and sky” image of size (198x198) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm

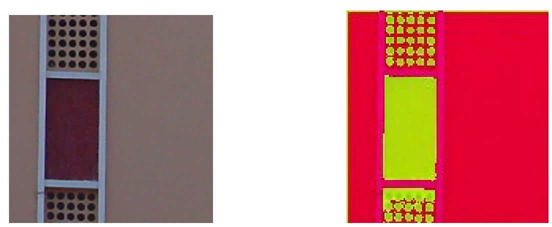


(a) (b) (c)

Figure 7. (a) Original “Building-wall” image of size (1024x1024) (b) Result obtained using Hybrid algo. (c) Convergence of SA and Hybrid algorithm

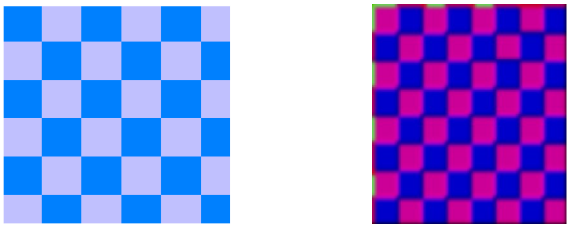
7. CONCLUSION

This paper addressed the problem of color image segmentation in a supervised framework. In this framework, it is assumed that one original image is available from a class of images from which the given observed image is derived. The segmentation problem is formulated as a pixel labelling problem. The pixel labels are estimated using MAP criterion. The MAP estimates are obtained by SA algorithm and found to take appreciable amount of time. In order to achieve faster convergence, a new hybrid algorithm is proposed to obtain the MAP estimates. This was developed based on the notions of local and global search strategies. It is observed that the proposed hybrid algorithm converges



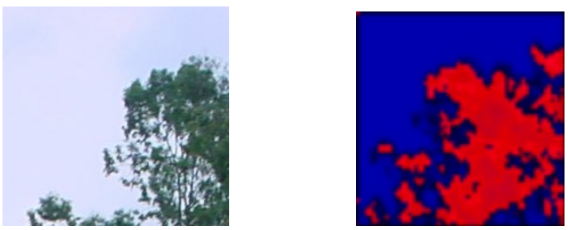
(a) (b)

Figure 8. (a)Original “Building-wall” image of size (1024x1024); (b) Reconstructed image at finer level of size (1024x1024)



(a) (b)

Figure 9. (a)Original "Checker-Board" image of size (512x512); (b) Reconstructed image at finer level of size (512x512)



(a) (b)

Figure 10. (a)Original "Tree and sky" image of size (512x512); (b) Reconstructed image at finer level of size (512x512)

much faster than that of SA. This computational time could further be reduced by adopting the multiresolution approach. The parameters are estimated at a coarse resolution and segmentation is achieved using MAP criterion at the coarse level. Segmentation at the finest resolution is obtained by reconstructing the segmented image from the coarse resolution to the finest resolution. We have used Gaussian Pyramid structure for multiresolution and hence the process used filtered some edge information. Hence, the segmented image at the coarse resolution missed some edge informations. The reconstructed image at the finest level also lost some edges. This price has been paid at the cost of very low processing time i.e. a few seconds. This scheme provides a stepping stone fro implementing the schemes in real-time environment. Currently, we are working on segmentation of color images in complete unsupervised framework and its real-time implementation.

	σ	ITER	Time(Sec.)	Algo
Fig.7(a)	8.33	1500	17637	SA
Fig.7(a)	8.33	50	2222	Hybrid
Fig.8(a)	6.33	1600	295	SA-Coarse
Fig.8(a)	6.33	60	17	Hybrid-Coarse

Table 1. Parameters for "Building-wall" image of size (1024x1024), $(\alpha = 0.0289 \; and \; \beta = 2.874)$

	σ	ITER	Time(Sec.)	Algo
Fig.5(a)	5.33	4000	6800	SA
Fig.5(a)	5.33	180	513	Hybrid
Fig.9(a)	3.33	4500	137	SA-Coarse
Fig.9(a)	3.33	200	7	Hybrid-Coarse

Table 2. Parameters for "Checker-Board" image of size (512x512), $(\alpha = 0.0352 \; and \; \beta = 4.03)$

	σ	ITER	Time(Sec.)	Algo
Fig.6(a)	4.33	1300	4704	SA
Fig.6(a)	4.33	100	420	Hybrid
Fig.10(a)	4.33	2000	62	SA-Coarse
Fig.10(a)	4.33	100	3	Hybrid-Coarse

Table 3. Parameters for "Tree and Sky" image of size (512x512), $(\alpha = 0.079 \; and \; \beta = 3.1)$

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