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# PARALLEL HYBRID TABU SEARCH ALGORITHM FOR IMAGE RESTORATION

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**Abstract— In this article a novel parallel hybrid algorithm is proposed for image restoration. The Image restoration problem is formulated as a Maximum a Posteriori (MAP) estimation problem. The noise free image is modeled as Markov Random Field Model. The MAP estimates are obtained by the proposed hybrid Tabu algorithms. The performance of the algorithm is enhanced by parallelizing the proposed hybrid algorithm. The results obtained using the proposed algorithm are compared with that of using Simulated Annealing algorithm and it was found that the former outperforms the later one. The results presented in this paper correspond to the serial implementation of parallel algorithm.**

## I. INTRODUCTION

Image restoration is one of the basic early vision problem which has been addressed for more than two decades [1], [2], [3], [4]. This problem can be viewed as extracting the noise free image *x* from the observed degraded image y . The image degradation can be attributed to blurring, noise contamination and camera nonlinearities etc. [1], [2]. The model-based approach has been extensively used in the literature to obtain the solution to the problem. Stochastic models in general and Markov Random models in particular have provided viable solutions to the above problem for quite sometime [1], [2], [3], [4]. Markov Random Field model, due to its potential features, has been used as the a priori model for images [1], [3]. We have modeled the noise free images as MRF models. The MRF or equivalently the Gibbs distribution in conjunction with the noise distribution provide the a Posteriori Distribution. In this piece of work, we have considered the degradation process as contamination with additive noise.

The associated model parameters in the model based approach may be assumed to be either known or unknown thus categorising as supervised or unsupervised methods. The effect of uncertainty in blurring has been investigated in [2] where the parameters have been selected on an adhoc basis. In [3] and [4], the MRF model parameters and the image are jointly estimated to obtain the noise free image.

In this paper, the noise free image is modeled as MRF model and the associated model parameters are either estimated *a priori* or assumed to be known. We have considered the MRF model with line field [1] that helps in preserving the edges. A simple degradation model is considered where we have assumed that the observed image is corrupted by additive white Gaussian noise. The image restoration problem is cast as a Maximum A Posteriori (MAP) estimation problem. Often the MAP estimates are obtained by Simulated annealing algorithm [5]. The algorithm is computationally expensive in the sense that it allows revisits of the solutions which have already been visited in the search space. This bottleneck is alleviated by incorporating the notion of Tabu search in the random strategy. Thus, we propose a hybrid algorithm exploiting the potentialities of the Tabu search and Simulated Annealing algorithm. The resulting guided search is based on the concept of minimum energy. In order to make the algorithm suitable from a practical standpoint, we have parallelized the proposed hybrid algorithm. This reduces the computational burden in the sense that the computational burden is equal to the computational burden of each unit in the context of parallelization. Since, we do not have a parallel machine, the proposed results presented correspond to the serial implementation of the proposed parallel algorithm. The results obtained are compared with that of the SA and it is found that proposed algorithm outperforms the SA. Although simulation was carried out for different cases, a few are presented for the sake of illustration.

## II. IMAGE RESTORATION PROBLEM

We have considered the following degradation model

$$Y = X + N \tag{1}$$

Where $Y$ is the observed random field, $X$ is the noise free image random field, $N$ is the Gaussian noise process. Let $y$ and $x$ denotes the realizations of observed image $Y$ and noise free image $X$ respectively. In (1) $X$ is modeled as MRF and hence $P(X=x|\phi)=(1/Z)e^{-U(x,\phi,l)}$ ,where $Z=\sum_x e^{-U(x,\phi)}$ is the partition function , $l$ is the line process, $\phi$ is the clique parameter and $U(x,\phi)$ is the energy function. We have formulated the restoration problem as MAP estimation problem. Thus, we consider the following optimality criterion

$$\hat{x} = \arg\max_x P(X = x \mid Y = y, \phi) \tag{2}$$

Using Bayes rule, (2) can be expressed as

$$\hat{x} = \arg\max_x \frac{P(Y = y \mid X = x, \phi)P(X = x \mid \phi)}{P(Y = y \mid \phi)} \tag{3}$$

Since $y$ is the observed image, the denominator is constant. Furthermore, we assume that noise is statistically independent of the signal. Using this assumption and the fact that $P(X=x)=(1/Z)e^{-U(x)}$ , (3) can be expressed as

$$\hat{x} = \arg\max_{x} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-\|y-x\|^2}{2\sigma^2}} e^{-U(x,\phi,l)} \quad (4)$$

Thus, (2) reduces to

$$\hat{x} = \arg\max_{x} e^{\frac{-\|y-x\|^2}{2\sigma^2}} e^{-U(x,\phi,l)} \quad (5)$$

In other words, (5) can be expressed as

$$\hat{x} = \arg\min_{x} \frac{\| y-x \|^2}{2\sigma^2} + U(x,\phi,l) \quad (6)$$

Often (6) is solved using Simulated Annealing Algorithm. Here we obtain the MAP estimate by solving (6) using the proposed hybrid algorithm and parallel hybrid Tabu algorithm.

## III. HYBRID ALGORITHM

Tabu search has been used for complex optimization problems [6], [7]. Recently this has been successfully employed to determine the optimal filter coefficient [8] and determining the boundary of a cell image[9]. Our algorithm is designed by exploiting the notion of Tabu search. By and large, the MAP estimate is obtained by employing Simulated Annealing algorithm. This algorithm although ameliorates the problem of local minima trapping, the algorithm visits the points in the solution space again and again. These frequent revisits increase the computational time. In order to alleviate such problems, we have introduced a set of Tabu moves which stores the recent moves. The next move in the Tabu search space is the one which has minimum energy and is not among earlier visited groups. Each Tabu move corresponds to an image and hence a Tabu image array is created. The next move is a Tabu move if it satisfies the aspiration condition. The aspiration condition is that even if the next move generated has higher energy, it would be accepted as with a probability. The Tabu image array is updated at each step. This process is repeated till the stopping criterion is met. The detail steps of the algorithm are as follows.

*Tabu Algorithm*

1. Initialize the initial temperature $T_{in}$ .
2. The initial image for the algorithm is the degraded image.
3. A Tabu list, i.e. Tabu image set is created to store the recent moves, i.e. the image estimates of the algorithm. The set is of fixed length.
4. From the current move or image the next Tabu image is generated.
   i)Perturb $x_{ij}(t)$ with a zero mean Gaussian Distribution with a suitable variance.
   ii)Evaluate the energy $U_p(x_{ij}(t+1))$ & $U_p(x_{ij}(t))$ . If $\Delta f = (U_p(x_{ij}(t+1)) - U_p(x_{ij}(t))) < 0$ ,assign the modified value as the new value. If $\Delta f > 0$, accept the $x_{ij}(t+1)$ with a probability (if $\exp(-\Delta f/T(x))>\text{random}(0,1)$) .
   iii)Repeat step 2 for all the pixels of the image.
5. Compute the power of the updated image x(t+1) as $P_{x(t+1)}$ and compare it with the powers of the tabu list named as Tabu energy if $P_{x(t+1)} < P_{Tabu}$ then x(t+1) is a Tabu image.
6. Aspiration condition : If $P_{x(t+1)} > P_{Tabu}$ , accept x(t+1) as Tabu image with probability
7. Update the Tabu list.
8. Decrease the Temperature according to the logarithmic cooling schedule.
9. Repeat step 4 – 9 for a fixed number of iterations.

## IV. PARALLEL HYBRID ALGORITHM

In the hybrid algorithm, the next move is decided based upon the computation of energy of all the possible Tabu moves. This incurs a substantial amount of computational burden. This is reduced by parallelizing the hybrid algorithm. The image is partitioned into a set of sub images, say for example(16×16), (32×32). The computation of energy is carried out over each sub image. The computation of energy for the Tabu moves are achieved in parallel. Thereafter, the total energy is computed by summing the individual ones. Thus, the possible Tabu moves are computed. If the next image is having minimum energy when compared with the Tabu set, then it is considered as a Tabu move. The next move with higher energy is also accepted with probability. The algorithm moves to the next point of minimum energy. Each move corresponds to an image of minimum energy. Thus, the notion of parallelism and guided search is incorporated into our algorithm. The steps of the algorithm are as follows.

*Parallel Tabu Algorithm*

1. Initialize the initial temperature $T_{in}$ .
2. The initial image for the algorithm is the degraded image.
3. A Tabu list, i.e. Tabu image set is created to store the recent moves, i.e. the image estimate of the algorithm. The set is of fixed length.
4. The image is partitioned into Subimages of size (16x16) and (32 x32).
5. For each sub image
   i)Perturb $x_{ij}(t)$ with a zero mean Gaussian Distribution with a suitable variane.
   ii)Evaluate the energy $U_p(x_{ij}(t+1))$ & $U_p(x_{ij}(t))$ . If $\Delta f = (U_p(x_{ij}(t+1)) - U_p(x_{ij}(t))) < 0$ ,assign the modified value as the new value. If $\Delta f > 0$, accept the $x_{ij}(t+1)$ with a probability (if $\exp(-\Delta f/T(x))>\text{random}(0,1)$) .
6. Repeat step 5 for all the subimages.
7. Compute the total energy of the image by adding the energies of the subimages.
8. Compute the power of the updated image x(t+1) as $P_{x(t+1)}$ and compare it with the powers of the tabu list named as Tabu energy if $P_{x(t+1)} < P_{Tabu}$ then x(t+1) is a Tabu image.
9. Aspiration condition : If $P_{x(t+1)} > P_{Tabu}$ , accept x(t+1) as Tabu image with probability
10. Update the Tabu list.
11. Decrease the Temperature according to the logarithmic cooling schedule.
12. Repeat step 4 – 9 for certain number of iterations.

## V. SIMULATION

In our simulation, we have considered the first order MRF model as the prior model for the image. The *a priori* model is

$$U(x,\phi,h,v)=\sum_{i,j}(\alpha((x_{i,j}-x_{i,j-1})^2(1-h_{i,j})+ (x_{i,j}-x_{i-1,j})^2(1-v_{i,j}))+\beta(h_{i,j}+v_{i,j})) \quad (7)$$

Where $x$ denotes the noise free image that is modeled as MRF, $h_{I,j}$ and $v_{I,j}$ represent the horizontal and vertical line processes attributed to edge preserving capability. $\alpha,\beta$ are the image model parameters. The corresponding a posteriori model is

$$U_p(x,\phi,h,v)=\frac{1}{2\sigma^2}\|y-x\|^2+U(x,\phi,h,v) \quad (8)$$

Although we have tested the two proposed algorithms for different images, for the sake of illustration, we present the results of an Ash-tray image of our laboratory and the LISA image. The two proposed algorithms are applied for Ash-tray image and the results are compared with that of the Simulated Annealing algorithm. The parameters used are : Initial temperature $Tin$=0.1, length of Tabu image array $L$=10, number of iterations K= 700.

In parallel hybrid Tabu algorithm the image is partitioned into 16 blocks. The images shown in Fig.1 correspond to Ash-tray image and the parallel hybrid algorithm. The *a priori* model parameters used for Ash-tray image are $\alpha$ =0.019 β=3.558. The algorithm was run for 700 iterations. Fig.1(*a*) shows the original image of size (200×250). Three algorithms were applied to a noisy image of SNR 15dB as shown in Fig.1(*b*). The restored image obtained by the parallel hybrid algorithm is shown in Fig.1(*c*) which is of SNR 22dB, thus improving the SNR by 7 dB. The SNR improvement with the number of iterations for all the three algorithms is shown in Fig.1(*d*). As observed from Fig.1(*d*), the hybrid algorithm accelerates faster than the parallel hybrid which in turn is faster than the SA algorithm. It is also clear from Fig.1(*d*) that for a given SNR, for example 20dB, hybrid algorithm takes approximately 60 iterations as opposed to SA achieving the same at around 150 iterations. The parallel hybrid algorithm also takes around 90 iterations to achieve a SNR of 20dB. Hence the hybrid algorithm is fastest among the three algorithms. The reason for the Parallel Tabu to be slower than the hybrid algorithm are two fold; (i) Interprocessor communication is not taken into account and partitioning results in the computation of energy which is close to the actual energy. (ii) The results correspond to the serial implementation.

Similar phenomenon is also observed in case of second example, that is LISA image as shown in Fig.2. The original image is shown in Fig.2(*a*) and the noisy image of 12dB is shown in Fig.2(*b*). The image model parameters are $\alpha$=0.0163 β=5.618. The number of iterations for this example is 400. The corresponding restored image of SNR=20dB is shown in Fig.2(*c*). The observations from Fig.2(*d*) are analogous to those obtained in case of the first example of Ash-tray image.

## VI. CONCLUSION

We have proposed two new algorithms using the notion of Tabu Search and Simulated Annealing algorithm for image restoration problem. It was found that the performance of the two proposed algorithms is superior to that of SA algorithm. The parallel hybrid algorithm will be the fastest among the three, if the algorithm is implemented in parallel machine. Future work aims at the parallel implementation of the proposed algorithm.

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Fig.1. (a)
(size = 200 x 250)
Original image

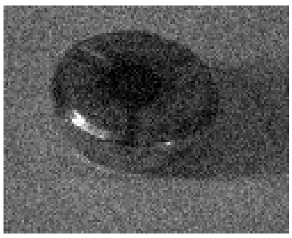

Fig.1.(b)
Noisy image
SNR=15dB

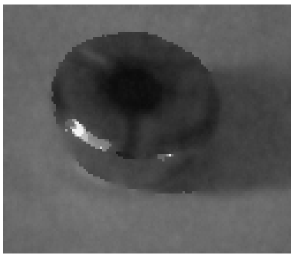

Fig.1. (c)
Restored image
SNR=22.0dB

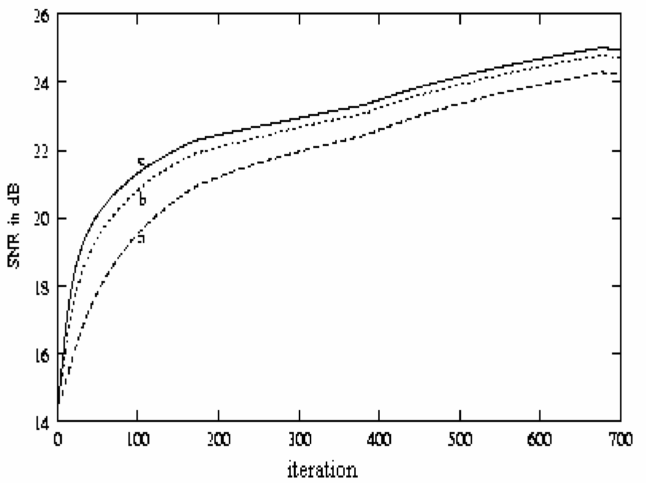


Fig.1. (d) a = SA Algorithm.
b = Parallel Hybrid Algorithm
c = Hybrid Algorithm

Fig.2. (a)
(size = 128 x 128)
Original image

Fig.2. (b)
Noisy image
SNR = 12dB

Fig.2. ( c )
Restored image
SNR =22.0dB

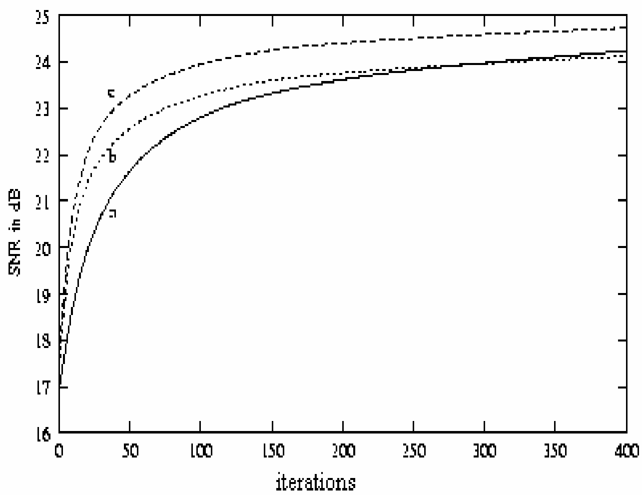


Fig.2. (d) a = SA Algorithm
b = Parallel Hybrid Algorithm
c = Hybrid Algorithm