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Inpainting in Color Images Based on Stochastic Model with Bayesian Approach

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Abstract – This paper introduces a novel approach, i.e. block oriented – restoration, based on a family of Full Range Autoregressive (FRAR) model to restore the information lost, and this adopts the Bayesian approach to estimate the parameters of the model. The Bayesian approach, by combining the prior information and the observed data known as posterior distribution makes inferences. The loss of information caused is due to errors in communication channels, through which the data are transmitted. Even if there is loss of a single bit in a block, it causes loss in the whol block and the impact may reflect on its consecutive blocks. In the proposed technique, such damaged blocks are identified, and to restore it a priori information is searched and extracted from undamaged regions of the image; this information and the pixels in the neighboring region of the damaged block are utilized to estimate the parameters. The estimated parameters are employed to recover the damaged block. The proposed algorithm takes advantage of the linear dependency of the neighboring pixels of the damaged block and takes them as source to predict the pixels of the damaged block. The restoration is performed at two stages: first, the lone blocks are restored; second, the contiguous blocks are restored. It produces very good results and is comparable with other existing schemes.

I. INTRODUCTION

This article addresses the problem of disocclusion or inpainting in color images. The basic idea is to fill in the gap of missing data in a form that it is non-detectable by an ordinary observer; this type of process is called inpainting. In last decade, the Internet and TV usage has rapidly increased and it causes traffic jam in data transmission. To avoid this problem, several image-coding algorithms have been developed to reduce the bit rate considerably for image and video representation, and transmission. Among them, block-based techniques have proved to be the most appropriate, for instance, Joint Photographic Experts Group (JPEG) [1], Motion Picture Expert Group (MPEG) [2] and H.261 [3]. The data may be corrupted while transmitting them through real-world communication channels, because the channels are not error free. Block-based image coding systems are vulnerable to transmission impairment. The loss of a single bit often results in loss of a whole block and may cause consecutive block losses [4]. This kind of degradation or damage occurs in a variety of domains of applied science and engineering such as visual communications, medical diagnostics, atmospheric remote sensing and astronomy. This motivated as to provide a novel technique which is block oriented.

The image restoration means recovering an original intensity distribution $f=\{f_S;s\in S\}$ defined over a 2-D square lattice S from its neighborhood or similar image region with pixels $g=\{g_S;s\in S'\subset S\}$.

Over a decade, numerous techniques have been developed to restore the original image from its degraded version. In image inpainting/disocclusion/restoration problems, the blind restoration technique has attracted many researchers [6-9]. In it, the major issue is to identify a priori knowledge about the image, point spread function (PSF), and incorporates them in the blind restoration process to minimize the severe lack of information [6]. The prior information of the PSF is not available in blind image restoration. First, the PSF is identified blindly and then restoration is performed [9].

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The model based approaches such as Autoregressive (AR) [5, 10], Autoregressive Moving Average (ARMA) [9] and Markov Random Field models [11] have become popular due to their simplicity and appropriateness of image restoration, in-painting and texture synthesis. Error concealment algorithm [4, 12-15] plays a significant role in image restoration problem and is known as low-pass filter, in which the missing information is masked to create subjectively acceptable image. Most techniques use Bayesian approach to estimate the parameters of the model a fore mentioned. The Bayesian analysis is performed in general by combining the prior information and the observed data known as the posterior distribution, from which all the inferences are made [16]. First, Morris [17] proposed the Bayesian approach to resolve this data fusion aspect of combining different sorts of prior information. This approach was subsequently used by many authors [16,18-20] in a unified framework that treats motion, missing data and noise jointly, and they concluded that the Bayesian approach yields better results compared with other techniques Wang et al 4 proposes the best neighborhood algorithm in which the following points are observed;

i) This algorithm will work for the periodic pattern textured images only, not for the stochastic pattern and structured images, since there is no guarantee for the same block to be repeated within a particular region.

ii) They have not fixed any threshold to decide on the best matching domain block to the range block. Instead they have selected the best one among the blocks belonging to the searching range block.

iii) So, the selected domain block may or may not be close to the range block.

To overcome these problems, a novel technique based on FRAR model with Bayesian approach, is proposed, which adopts block oriented restoration in color images. In the proposed approach, three different types of blocks, namely damaged block, range block and prior-information block are used to identify the prior information. The best- matched block of the range block is searched throughout the whole image. The best-matched block is called prior-information block, and the information available with that block is utilized to estimate the parameters of the FRAR model. Based on the estimated parameters and the pixels in the neighboring region of the damaged block, the pixels in the damaged block are predicted. The obtained results are compared with the existing results of the error concealment algorithms such as without concealment, de-concealment, direct BNM and 1-order BNM algorithms.

II. THE PROPOSED MODEL

Let $\{h(k,l),(1 \le k,l \le M)\}$ be a set of pixel values in a 2-D monochrome image. In this article, it is assumed that $\{h(k,l)\}$ obeys the Markov properties [22-24]. Hence, based on the definitions, the given image is modeled as an Autoregressive (AR) random field. The restoration of the corrupted image region can be performed by utilizing the information available on the uncorrupted regions. Thus, based on the above definitions and the properties of the AR model, it is concluded that an AR model is most appropriate for restoration problem. The main properties of the AR model: (i) future values may depend on the present and the whole past; (ii) future values may not depend on the present and a few past values alone; (iii) facilitates to describe both short-term and long-term correlations. Therefore, this paper utilizes the properties to restore the damaged blocks (assumed to be future values as per properties) from its neighboring region (assumed to be past values as per properties), because the image region is mostly linearly dependent (correlated).

Let f be the image region to be restored, which is unknown distribution of some spatially varying process. Most authors approached the restoration problem by incorporating prior information about the shape and regularity of the objects of interest using the Bayesian approach [25-29]. As discussed in section 1, the LSE and MLE methods are not satisfactory. Hence, this article adopts, the Bayesian approach to estimate the image region f by considering the likelihood function $l(f)$, which gives the conditional distribution of the pixels in undamaged region given the pixels in the damaged block, i.e. $Pr(g/f)$ and the prior information obtained from the prior-information block, $\pi(g)$. The joint posterior distribution $Pr(f/g) \propto Pr(g/f)\pi(g)$ is obtained by using these two components and the Bayes' rule. By keeping all these points, a model is proposed as in equation (2), a family of Full Range Autoregressive (FRAR) model:

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$$f(k,l) = \sum_{r=1}^{M}\left(\frac{1}{n}\sum_{s=1}^{M}\Gamma_r\ g(k+r,\ l+s)\right) + \varepsilon(k,l) \quad (2)$$

where, $\Gamma_r = \dfrac{K\sin(r\theta)\cos(r\phi)}{\alpha^r}$ (2a)

$f(k,l)$ at location (k,l) represents the pixels to be predicted in the damaged block, and it extracts the linear combination of gray values of its neighboring $g(k+r,l+s)$ pixels through a set of coefficients Γ_r; r and s represent associated neighboring pixels; n represents a set of pixels in a row or column of the neighboring region to the damaged block; Γ_r is a set of coefficient values which characterize the dependency of a pixel on its neighbors; the coefficient is computed using a set of real parameters K, α, θ and ϕ, which are estimated based on the neighboring pixels and the prior information extracted from the prior-information block; $\varepsilon(k,l)$ is an independent Guassian random variable with mean zero and variance $\sigma^2>0$. The pixels in the damaged block are predicted by applying the coefficients $\Gamma_r s$ in equation (2).

It is interesting to note that some of the models used in the previous works, that is, white noise, autoregressive finite order and infinite order models can be regarded as a special case of the proposed model. Thus,

(i) if we set θ = 0, then the FRAR model reduces itself to the white noise process.
(ii) when α is large, the coefficients Γ_rs become negligible as 'r' increases. So the FRAR model reduces to AR(r) model approximately for a suitable value of r, where r is the order of the model.
(iii) when α is chosen to be less than one, then the FRAR model becomes an explosive infinite order AR model.

The fact that $f(k,l)$ has regression on its neighborhing pixels gives rise to the terminology of autoregressive process. However, the dependence of $f(k,l)$ on its neighboring pixels may be true to some extent. In fact, the process is Gaussian under the assumption of ε(*k, l*)s are Gaussian and its probabilistic structure is completely determined by its second or higher order properties. Second order properties meant for the proposed FRAR model is asymptotically stationary up to order two, provided 1– α < K < α – 1. The range of the parameters of the model are set as with the constraints K ∈ R, α > 1, 0 < θ < π, 0 < ϕ < π/2.

III. PARAMETER ESTIMATION

In order to experiment the proposed FRAR model, we must estimate the parameters K, α, θ and ϕ. The parameters are estimated by using: (i) the pixel values belonging to the prior-information block, which are treated as prior information and used to estimate the hyper parameters β, ν, and δ; (ii) the pixels in the neighboring region of the damaged block. The numerical integration technique and the Bayesian methodology [30,31] are adopted to estimate the parameters. The hyper parameter means the parameters of the prior distribution of the actual model parameters K, α, θ and ϕ. Only for the computational purpose, the pixel values are arranged as one-dimensional vectors {*X*(t), t = 1,2,3, . . . , N ($M \times M = M^2 = N$)}. Since the error term ε(*k, l*) in equation (2) is independent and identically distributed Gaussian random variable, the joint probability density function of the stochastic process {*X*(t)} is given by

$$\Pr\left(X/\Theta\right) \propto \left(\sigma^2\right)^{-N/2} \exp\left[-\frac{1}{2\sigma^2}\sum_{t=1}^{N}\left\{X_t - K\sum_{r=1}^{N}S_r X_{t-r}\right\}^2\right] \quad (3)$$

where $X = (X_1, X_2, \ldots, X_N)$; $\Theta = (K, \alpha, \theta, \phi, \sigma^2)$ and

$$S_r = \frac{\sin(r\theta)\cos(r\phi)}{\alpha^r}.$$

By expanding the square in the exponent, we get

$$\Pr\left(X/\Theta\right) \propto \left(\sigma^2\right)^{-N/2} \exp\left[-\frac{1}{2\sigma^2}\left\{T_{00} + K^2\sum_{r=1}^{N}S_r^2 T_{rr} + 2K^2\sum_{\substack{r,s=1\\ r<s}}^{N}S_r S_s T_{rs} - 2K\sum_{r=1}^{N}S_r T_{0r}\right\}\right] \quad (4)$$

where $T_{rs} = \sum_{t=1}^{N} X_{t-r}X_{t-s}$, $r,s = 0,1,2,\ldots,N$

The above joint probability density function can be written as

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$$\Pr\left(X/_{\Theta}\right) \propto \left(\sigma^2\right)^{-N/2} \exp\left[-\frac{Q}{2\sigma^2}\right] \qquad (5)$$

where

$$Q = T_{00} + K^2 \sum_{t=1}^{N} S_r^2 T_{rr} + 2K^2 \sum_{\substack{r,s=1\\ r<s}}^{N} S_r S_s T_{rs} - 2K \sum_{r=1}^{N} S_r T_{0r}$$

$K \in R$, $\alpha > 1$, $0 < \theta < \pi$, $0 < \phi < \pi/2$ and $\sigma^2 > 0$.

The prior distribution of the parameters K, α, θ, ϕ and σ^2 is assigned as follows:

1. In the proposed FRAR model, α represents the strength of the linear dependency of $f(k,l)$ on its neighboring pixels. The dependency decreases slowly while the spatial distance increases. The dependency of $f(k,l)$ on its neighborhoods is converged to zero beyond a certain limit. So, in this case α is set to greater than zero, which leads to convergence. Generally, the starting point of the exponential distribution is zero, but in this case it starts from above 1 i.e. α > 1. On these bases it is assumed that α is distributed as the displaced exponential distribution with parameter β, i.e.

$$\Pr(\alpha) = \beta \exp(-\beta(\alpha-1))\ ;\ \alpha>1;\ \beta>0 \quad (6)$$

2. The variance σ^2 of the white noise among the pixels is minimum and is inversely proportionate. Hence it has the inverted gamma distribution with parameter ν and δ. The parameter ν is shape parameter and δ is called a scale parameter. The gamma distribution tends to Gaussian distribution while the number of observations is large.

$$\Pr(\sigma^2) \propto \exp(-\nu/\sigma^2)\ (\sigma^2)^{-(\delta+1)}\ ;\ \sigma^2>0;\ \nu,\delta>0 \quad (7)$$

1. θ and ϕ are associated with *sine* and *cosine*, that are circular functions and their values range from 0 to 1. K is a real value function. Hence it is assumed that these parameters are uniformly distributed over their domains.

   Pr(K, θ, ϕ) = C, a constant ;

   $K \in R$, $0 < \theta < \pi$, $0 < \phi < \pi/2$

So, the joint prior density function of Θ is given by

$$\Pr(\Theta) \propto \beta \exp(-\beta(\alpha-1) - \nu/\sigma^2)(\sigma^2)^{-(\delta+1)}\ ; \quad \sigma^2>0,\ \alpha>1,\ 0<\theta<\pi,\ 0<\phi<\pi/2. \quad (8)$$

Using (5), (8) and Bayes rule, the joint posterior density of K, α, θ, ϕ and σ^2 is obtained as

$$\Pr\left(\Theta/_{X}\right) \propto \exp(-\beta(\alpha-1))\exp(-1/2\sigma^2)(Q+2\nu)\left(\sigma^2\right)^{-\left(\frac{N}{2}+\delta+1\right)}; \quad (9)$$

$K \in R$, $\alpha > 1$, $0<\theta<\pi$, $0<\phi<\pi/2$ and $\sigma^2 > 0$.

Integrating (9) with respect to σ^2, the posterior density of K, α, θ and ϕ is obtained as

$$\Pr(K, \alpha, \theta, \phi/X) \propto \exp(-\beta(\alpha-1))(Q+2\nu)^{-\left(\frac{N}{2}+\delta\right)} \quad (10)$$

$K \in R$, $\alpha>1$, $0<\theta<\pi$, $0<\phi<\pi/2$

where

$$[Q+2\nu] = \left[\left(K^2 \sum_{r=1}^{N} S_r^2 T_{rr} + 2K^2 \sum_{\substack{r,s=1\\ r<s}}^{N} S_r S_s T_{rs} - 2K \sum_{r=1}^{N} S_r T_{0r}\right) + T_{00} + 2\nu\right] \quad (11)$$

That is,

$$(Q+2\nu) = aK^2 - 2Kb + T_{00} + 2\nu,$$

$$= C\left[1 + a_1(K-b_1)^2\right] \quad (12)$$

$$C = T_{00} - \frac{b^2}{a} + 2\nu \quad (6)$$

where

$$a = \sum_{r=1}^{N} S_r^2 T_{rr} + 2 \sum_{\substack{r,s=1\\ r<s}}^{N} S_r S_s T_{rs}$$

$$b = \sum_{r=1}^{N} S_r T_{0r}\ ;\ a_1 = \frac{a}{C}\ ;\ b_1 = \frac{b}{a}$$

Thus, the above joint posterior density of K, α, θ and ϕ can be rewritten as

$$\Pr(K, \alpha, \theta, \phi / X) \propto \exp(-\beta(\alpha-1))\left[C\left\{1 + a_1(K-b_1)^2\right\}\right]^{-d} \quad (13)$$

$K \in R$, $\alpha>1, 0<\theta<\pi$, $0<\phi<\pi/2$

where, $d = \frac{N}{2} + \delta$

This shows that, given α, θ and ϕ the conditional distribution of K is 't' distribution located at b_1 with (2d–1) degrees of freedom.

The proper Bayesian inference on K, α, θ and ϕ can be obtained from their respective posterior densities. The joint posterior density of α, θ and ϕ, that is, Pr(α, θ, ϕ /

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X), can be obtained by integrating (13) with respect to K. Thus, the joint posterior density of α, θ and ϕ is obtained as

$$\Pr(\alpha, \theta, \phi / X) \propto \exp(-\beta(\alpha-1))C^{-d}\, a_1^{-1/2}$$
$$\alpha > 1,\ 0 < \theta < \pi,\ \ 0 < \phi < \pi/2$$

(14)

The posterior density of α, θ and ϕ in equation (14) is a complicated function and is analytically not solvable. Therefore, we can find the original posterior density of α, θ and ϕ numerically from the joint density function expressed in equation (14) as follows:

$$\left.\begin{aligned} \Pr(\alpha) &\propto \iint \Pr(\alpha, \theta, \phi / X)\, d\theta\, d\phi \\ \Pr(\theta) &\propto \iint \Pr(\alpha, \theta, \phi / X)\, d\alpha\, d\phi \\ \Pr(\phi) &\propto \iint \Pr(\alpha, \theta, \phi / X)\, d\alpha\, d\theta \end{aligned}\right\} \quad (15)$$

The point estimates of the parameters α, θ and ϕ may be taken as the means of the respective posterior distribution i.e. posterior means. With a view to minimize the computations, we first obtain the posterior mean of α numerically. Then fix α at its posterior mean and evaluate the conditional means of θ and ϕ. We fix α, θ and ϕ at their posterior means respectively and then evaluate the conditional mean of K.

Thus, the estimates are

$$\left.\begin{aligned} \hat{\alpha} &= E(\alpha) \\ (\hat{\theta}, \hat{\phi}) &= E(\theta, \phi / \alpha = \hat{\alpha}) \\ \hat{K} &= E(K / \hat{\alpha}, \theta = \hat{\theta}, \phi = \hat{\phi}) \end{aligned}\right\} \quad (16)$$

The estimated parameters K, α, θ and ϕ are used in equation (2a) to compute the coefficients Γ_rs of the FRAR model, which are utilized to restore the damaged block.

IV. DAMAGED BLOCK AND PRIOR INFORMATION IDENTIFICATION

To identify the damaged blocks in the corrupted input image, the image is divided into various blocks of size 8×8 and the statistics mean and variance are computed on each block and that are applied in the confidence interval expressed in equation (1). The value of σ^2 is compared to that of the lower and upper limits as in equation (1). If the σ^2 is less than the lower point then the block is assumed to be damaged because most values in the damaged block are nearer close or same, so there exist less variation among the pixels in the damaged block; if the σ^2 is greater than the upper point then the block is assumed to be partially damaged (combination of damaged and undamaged blocks) because the pixel values are in the low and high ranges (i.e. 0 to 255), so there exist high variation; otherwise, the block is treated as undamaged because the pixels belong to the group of moderate intensity values, so there exist moderate variation. In the case of partially damaged block, the region growing technique [28] is adopted to identify the boundary of the damaged block.

$$\frac{ns^2}{\chi_n^2(\alpha/2)} \le \sigma^2 \le \frac{ns^2}{\chi_n^2(1-\alpha/2)} \quad (1)$$

where, $s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$, $\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2$,

$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$, $\chi_n^2(\alpha/2)$-Chi-square distribution with *n* d.f. and significance level α; $\chi_n^2(\alpha/2)$ is the lower α point and $\chi_n^2(1-\alpha/2)$ is the upper α point.

To identify a prior information, the region surrounding the damaged block is selected and is known as range block with size 20×20. The structure of the range block is depicted in Figure 2. The $\bar{x}$ and σ of the pixels in the undamaged region of the range block are computed. Initially, two blocks with same size of the range block are selected arbitrarily, and $\bar{x}$ and σ of the pixels in those blocks are computed. These values are compared to that of $\bar{x}$ and σ of the uncorrupted region of the range block. The nearest values to the range block and the corresponding block are marked. Now, another block is considered, the $\bar{x}$ and σ are computed. Again, the nearest between the two sets (one set of values corresponds to the marked block, and the other set of values corresponds to the current block) of values to the range block is found. This process is continued for the entire image. Finally, the nearest $\bar{x}$ and σ to the $\bar{x}$ and σ of the range block is identified, and the corresponding block is marked as prior-information block. The information available with the prior-information block is considered as prior information, and are utilized to

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estimate the hyper-parameters of the prior distributions of the FRAR model parameters. The searching and matching methodology of the prior information is illustrated in Figures 1. A detailed procedure to identify the damaged block and the prior information is presented in an algorithmic form in section 5.

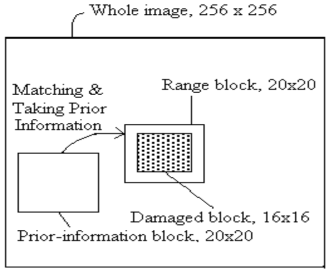

Figure 1. Structure of the searching technique

Based on the prior-information and the pixels in the neighboring region, the parameters of the FRAR model are estimated. The proposed model is employed to restore the damaged block by using the pixels in the neighboring region as source. The proposed restoration model is discussed in detail in the next section.

V. IMAGE RESTORATION

The proposed model takes advantage of the linear dependency among the pixels in a particular region. The estimated coefficients Γ_rs and the pixels in the neighboring region are utilized to restore the damaged block, where the layer 1 (outermost layer – pixels) of the damaged block is predicted first, and then the layer 2 is predicted. This process is continued for the remaining layers of the damaged block. For instance, to predict a pixel that belongs to the layer 1, a small image region (3×3) is considered, which is adjacent to and centered around to the pixel to be predicted (as illustrated in Figure 3). A set of pixels in the immediate neighboring row or column of the damaged block is given maximum weight (order one); the pixels in the adjoining row or column (order two) are given lesser weight than the previous (order one); and the following rows or columns are given lesser weight (order three) than the previous (order two). This paper only considers the first three neighboring rows or columns (up to third order). The methodology adopted to restore the pixels of the damaged block is illustrated in Figure 2.

In order to implement the concept depicted in Figure 2, the model in equation (2) is restructured as in equation (17) if r < k; r > k,

$$f(k,l) = \sum_r \left(\frac{1}{3} \sum_s \Gamma_{|r|}\ g(k+r,\ l+s) \right) + \varepsilon(k,l) \quad (17)$$

with constraints,

$$\begin{bmatrix} -1 \le s \le 1 \\ -1 \le r \le -3 \quad \text{if } r < k \end{bmatrix} \text{ and } \begin{bmatrix} -1 \le s \le 1 \\ 1 \le r \le 3 \quad \text{if } r > k \end{bmatrix}$$

and the same model is restructured as in equation (18) if s < *l*; s > *l*,

$$f(k,l) = \sum_s \left(\frac{1}{3} \sum_r \Gamma_{|s|}\ g(k+r,\ l+s) \right) + \varepsilon(k,l) \quad (18)$$

with constraints,

$$\begin{bmatrix} -1 \le r \le 1 \\ -1 \le s \le -3 \quad \text{if } s < l \end{bmatrix} \text{ and } \begin{bmatrix} -1 \le r \le 1 \\ 1 \le s \le 3 \quad \text{if } s > l \end{bmatrix}$$

where, $$\Gamma_{(\bullet)} = \frac{K\, sin(r\theta)\, cos(r\phi)}{\alpha^r}$$

(19)

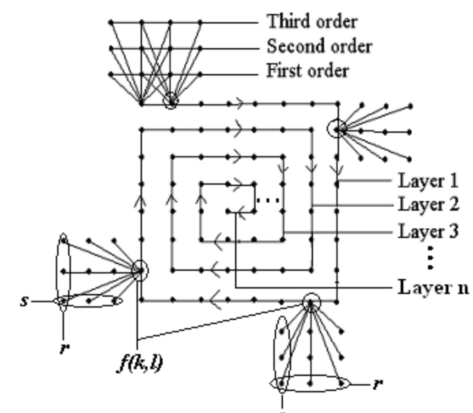

Figure 2. Structure and restoration technique of damaged block

VI. EXPERIMENTS AND RESULTS

In order to experiment the proposed FRAR model, different types of color images of size 256 x 256 are considered. Due to the space constraints, for sample, the lena image is presented here. The color image is segregated into RGB colors. On each color image, i.e. RGB color images, the damaged blocks and the prior

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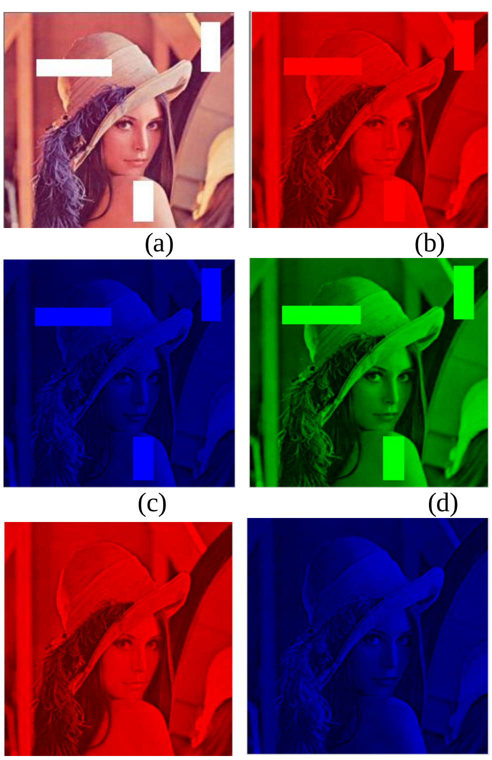
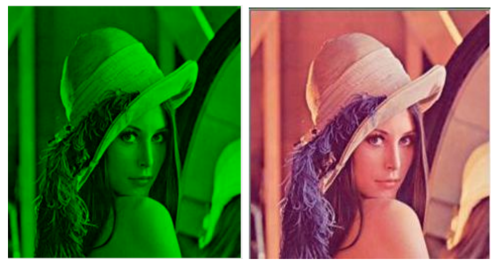
information are identified as discussed in section 4. Based on the prior information and the pixels in the neighboring region of the damaged block, the parameters K, α, θ and ϕ are estimated. Applying the parameters in equation (2a), the coefficients Γ_rs are computed, and employed to predict the pixels of the damaged block with the use of pixels in the neighboring region as discussed in section 5. The restoration process is performed at two stages: (i) lone blocks are identified and restored; (ii) contiguous blocks are restored. Now, the restored red, green and blue color images are synthesized into RGB color image. The experiment is conducted at various levels of loss of rates ranging from 5% to 15%. The quantitative measures such as PSNR and MSE are computed to the corresponding loss of rates to evaluate the restored image, and they are compared with the existing schemes. The results obtained at various levels of loss of rates are presented in Table 1. The obtained outputs of the experiment conducted on Lena image are shown in below Figure.



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



(g) (h)

(a) damaged block of lena image (b) segregated red color of lena image (c) segregated blue color (d) segregated green color (e) restored red color (f) restored blue color (g) restored green color (h) combination of restored red blue and green color gives color image which is similar to original image.

TABLE 1

PSNR (in dB) values for performance of different types of schemes with block loss rates ranging from 5% to 15% for lena image (values within brackets represent MSE)

Types of Algorithms	Block Loss Rate				
	5%	7.5%	10%	12.5 %	15%
Direct BNM	39.0	36.3	35.7	33.6	32.3
1-order BNM	39.6	37.6	37.1	35.0	33.2
Proposed Scheme	**43.2 (3.11)**	**42.4 (3.74)**	**40.8 (5.41)**	**38.6 (8.98)**	**36.1 (15.96)**

VII. CONCLUSION

This paper adopts an algorithm based on FRAR model and the Bayesian approach to estimate the parameters of the model, which is employed to restore the damaged blocks. The best matching block of the damaged block is searched throughout the whole image. The information available in the best matching block is extracted and used as prior information for actual parameters of the model. The parameters are estimated based on the prior information and the pixels in the neighboring region of the damaged block. The parameters are utilized to restore the damaged block. The proposed algorithm takes advantage of linear dependency of the neighboring pixels of the damaged block and takes them as source to predict the pixels in the damaged block. A structured lena image is considered during the experiment. The performance of the proposed technique is evaluated in terms of quantitative and qualitative measures. The experimental results clearly show that the proposed restoration scheme yields good results. The obtained results are comparable with the existing methods.

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