COLOR IMAGE IDENTIFICATION AND RESTORATION

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ABSTRACT. Image identification involves estimating the properties of an imperfect imaging system from an observed image prior to the restoration process. In this paper we present a novel identification technique for multichannel image processing using the maximum likelihood estimation (ML) approach. The image is represented as an autoregressive (AR) model and blur is described as a continuous spatial domain model, to overcome some major limitations encountered in other ML methods. Cross-spectral and spatial components, which are inherent to multichannel imaging systems, are also incorporated in the model to improve the overall performance. Also, it is shown that blur extent can be optimally identified from noisy color images that are degraded by uniform linear motion or out-of-focus blurs. The novelty of this approach in identifying the blur of multichannel images is a major contribution in producing visually acceptable results which is significant for higher processing levels.

1. INTRODUCTION

Multichannel images refer to the type of data obtained from multiple frequency bands, multiple time frames, or multiple sensors. Such images have numerous applications in practice, such as, medical diagnosis, forensic sciences, industrial automation, space and satellite imagery. For the sake of terminology, we are going to use the term multichannel throughout this paper to refer to an image obtained by an imaging system that uses more than one sensor for the same scene.

Processing multichannel images, such as smoothing, restoration, and enhancement is an important step before any further use or analysis. The degradation sources for the single channel case, such as noise and blur, apply to the multichannel case, too. However, an additional and important type of degradation that is natural to the multichannel imaging is the cross-channel or cross-spectral degradation. For example, the overlapping in the cutoff frequency characteristics of the detectors results in cross-spectral mixing of adjacent spectral bands [1].

As in the single channel case, the multichannel identification techniques have not received much attention as the restoration techniques have. As a matter of fact, even the restoration techniques for multichannel imaging have not received much attention. Although it seems a straightforward extension of the single channel methods, the lack of multichannel image processing theories, the complexity of the computation involved, and the consideration of the cross-spectral effects between frames make the problem more difficult.

In general, restoring each channel independently does not necessarily produce useful results because of neglecting the information between the channels. Following this approach, Bescos *et al*. [2] applied conventional restoration techniques to individual color components without using the cross-channel information. Also, Angwin and Kaufman [3] presented adaptive filtering for color images without taking into account the correlation between the color components. This resulted in a suboptimal solution. Thus, solutions which are optimal for the single channel case may be suboptimal for the multichannel image when restored independently [1]. One of the successful approaches to overcome this problem is to model the correlation between the channels and incorporate it explicitly into the filtering procedure. Pavlovic' and Tekalp [4] employed this approach using the Kalman filtering and least squares parameter identification of the image parameters. Ozkan *et al.* [5] applied this approach to Wiener restoration filters. In an extensive study, Galatsanos [6] presented and applied this approach using an efficient and feasible computation algorithms including Wiener, Kalman, and least squares techniques, however, blur parameters were assumed to be known. In [7], a multichannel Wiener filter was proposed in both the spatial and frequency domains that showed a reduction in computation. Almost all of these researches deals with restoration techniques of multichannel images rather than the identification process. Up-to-date, techniques that study the multichannel identification problem are very limited. Among the rare papers in this subject is the work of Pavlovic *et al.*[8]. Thus, this area needs to be extensively studied.

In this paper we will be considering blur identification of multichannel images using the maximum likelihood (ML) parametric approach by modeling the blurring process in the continuous spatial domain. Since this modeling overcame the limitations of the existing ML techniques in the monochrome case as demonstrated in [9,10], it is shown here that it also behaves similarly in the multichannel one, thus improving the identification and the restoration process.

Considering the two familiar types of blur that can be represented in a closed form parametric description in the continuous domain, namely, the 1-D uniform motion blur and the 2-D out of focus blur, we will show how to identify the blur extent from noisy color images. Then, by implementing some restoration methods available for multichannel imaging, the identified parameters will be used to restore the original image. Employing the cross-channel information will be an important factor in the modeling. It is shown that incorporation of these components produces more accurate results.

2. MODELING AND FORMULATION

Following the AR image and observation models formulations given in [4,8,11], we consider here the multichannel modeling where the image and observation models for the *pth* channel are represented as

$$s_p(m,n) = \sum_{q=1}^{N} \sum_{R_{pq}} c^{pq}(k,l)\, s_q(m-k, n-l) + w_p(m,n) \tag{1}$$

$$r_p(m,n) = \sum_{q=1}^{N} \sum_{(k,l)\in S_h} h^{pq}(k,l)\, s_q(m-k, n-l) + v_p(m,n) \tag{2}$$

represent the model $c^{pq}(k,l)$ is the number of spectral channels, N respectively, where denotes the support of the coefficients R_{pq} channels, q^{th} and p^{th} coefficients coupling the is the zero $w_p(m,n)$ channel and q^{th} is the undistorted image for the $s_q(m,n)$, $c^{pq}(k,l)$ channel. Equations (1) and (2) can be written in a p^{th} mean white Gaussian noise for the matrix form as

$$\mathbf{s}_p = \mathbf{C}^{pq}\mathbf{s}_p + \mathbf{w}_p \tag{3}$$

$$\mathbf{r}_p = \mathbf{H}^{pq}\mathbf{s}_p + \mathbf{v}_p \tag{4}$$

are the lexicographic order of the corresponding terms in $\mathbf{v}_p$, and $\mathbf{w}_p$,$\mathbf{r}_p$, $\mathbf{s}_p$ where,
represent the appropriate ordering of the model and blur $\mathbf{H}^{pq}$ and $\mathbf{C}^{pq}$equations (1) and (2),
coefficients, respectively. Further, we may write the set of equations (3) and (4) in
lexicographic orders to get

$$\boldsymbol{s} = \boldsymbol{Cs} + \boldsymbol{w} \quad (5)$$

$$\boldsymbol{r} = \boldsymbol{Hs} + \boldsymbol{v} \quad (6)$$

, and $\mathbf{w}_p$, $\mathbf{r}_p$, $\mathbf{s}_p$ are the lexicographic order of $\boldsymbol{r},\boldsymbol{s},\boldsymbol{v},$ and $\boldsymbol{w}$ vectors $NM^2 \times 1$ where now, the
is the image model matrix $\boldsymbol{C}$, respectively, and where $q = 1,2,\ldots,N$ and $,p = 1,2,\ldots,N$, for $\mathbf{v}_p$
. $(NM^2 \times NM^2)$ is the degradation or blur matrix, and both are block matrices of size $\boldsymbol{H}$ and
Following the procedure used to derive the PDF of the observed image for the single channel
,which is also Gaussian, as $\boldsymbol{r}$ case [9,12], we may now express the PDF of

$$p(\boldsymbol{r};\Theta) = \frac{1}{\sqrt{(2\pi)^{N^2}|\boldsymbol{P}_{rr}|}} \exp\left(\frac{1}{2}\boldsymbol{r}^t\boldsymbol{P}_{rr}^{-1}\boldsymbol{r}\right) \quad (7)$$

$\boldsymbol{P}_{rr}$. $h_{i,j}(k,l), c_{ij}(m,n), \sigma^2_{v_{ij}}, \sigma^2_{w_i}$ represents the unknown parameters, Θ where now, the vector
are computed $\boldsymbol{P}_{rr}$ is the covariance matrix of block structure where elements of each block of
as

$$\mathbf{P}^{ij}_{rr}(k,l) = E[r_i(m,n)r_j(m+k,n+l)] \quad (8)$$

is not $\boldsymbol{P}_{rr}$ is the number of channels. Notice that the matrix of N where $i,j = 1,2,\ldots,N$ for
, where cross-spectral components are not the same $\boldsymbol{C}$ Toeplitz because of the structure of
. $\mathbf{P}^{ij}_{rr} = [\mathbf{P}^{ij}_{rr}]^t$ is a Toeplitz matrix and $\boldsymbol{P}_{rr}$ in each channel. However, each block element of
as $\boldsymbol{H}$ and $\boldsymbol{C}$ in terms of $\boldsymbol{P}_{rr}$ We may now express

$$\begin{aligned} \boldsymbol{P}_{rr} &= E[\boldsymbol{rr^t}] \\ &= E[\{\boldsymbol{H}(\boldsymbol{I} - \boldsymbol{C})^{-1}\boldsymbol{w} + \boldsymbol{v}\}\{\boldsymbol{H}(\boldsymbol{I} - \boldsymbol{C})^{-1}\boldsymbol{w} + \boldsymbol{v}\}^t] \end{aligned} \quad (9)$$

which can be simplified as

$$\boldsymbol{P}_{rr} = \boldsymbol{H}(\boldsymbol{I} - \boldsymbol{C})^{-1}\boldsymbol{P}_{ww}(\boldsymbol{I} - \boldsymbol{C})^{-t}\boldsymbol{H}^t + \boldsymbol{P}_{vv} \quad (10)$$

2.1 Maximum Likelihood Estimator

The maximum likelihood estimate is obtained by maximizing the LF [10,12]. Using (7) and
and simplifying, the ML identification problem can Θ (10), dropping all terms independent of
be expressed as

$$\begin{aligned} \mathrm{L}(\Theta) &= -\log\{p(\boldsymbol{r};\Theta)\} \\ &= -\{\log(|\boldsymbol{P}_{rr}|) + \boldsymbol{r}^t\boldsymbol{P}_{rr}^{-1}\boldsymbol{r}\} \end{aligned} \quad (11)$$

The parameters that maximize the LF can be obtained by equating all the partial derivatives of the LF to zero. However, this optimization problem is so extensive because of the number of unknowns involved. Therefore some simplifications are necessary. We will make the , are estimated using the least $\sigma^2_{w_i}$ and $c_{ij}(m,n)$ assumption that the model coefficients, , will be estimated as the variance of $\sigma^2_{v_{ij}}$ square procedure. Also, the observation noise, a uniform region in the different channels. Further, we make the following practical assumption. We assume that the cross channel blur is not significant. This means that although the channels exhibit cross-correlation, the contribution of the blur to this correlation is minimal or negligible. The major contributor to the cross-correlation is the image signal. Our experimental results demonstrate this.

To be able to compute the conditional likelihood function, we make use of the structure of and apply the Toeplitz-to-circular approximation through the DFT for each block $\boldsymbol{P}_{rr}$. Thus, the CLF can be written in the frequency domain as $\boldsymbol{P}_{rr}$ element of

$$\mathrm{L}(\Theta) = -\sum_k \sum_l \left\{ \log(\left|\mathbf{S}_{r_p r_p}(k,l)\right|) + \frac{1}{M^2} \frac{\left|R_p(k,l)\right|^2}{\mathbf{S}_{r_p r_p}(k,l)} \right\} \tag{12}$$

Following the formulation used in [9,10], we first express the blur PSF as a function of , as p in the continuous domain for channel $\Theta = [\theta_1, \theta_2, \ldots, \theta_n]$ parameters

$$h_p(x,y) = h_p(x,y;\Theta) \quad \text{for} \quad (x,y) \in \Re_p(\Theta) \tag{13}$$

. The observed image in continuous p denotes the PSF support for channel $\Re_p(\Theta)$ where domain can be written as

$$r_p(m,n) = \int_{\Re(\Theta)} h_p(\xi,\eta;\Theta) s(m\Delta x - \xi, n\Delta y - \eta) d\xi d\eta + v(m,n) \tag{14}$$

denote the Δy and Δx, where the two intervals $(x,y) = (m\Delta x, n\Delta y)$ by sampling at the points denotes discrete spatial domain (m,n) horizontal and vertical sampling distances, respectively, . This accuracy in this form $r_p(x,y)$ are the observed samples of $r_p(m,n)$ coordinates, and of modeling overcomes the bandliminting assumption of the discrete model. Also, it will enable us to differentiate with respect to the variable appearing in the integration limits for , $P_{r_p r_q}(i,j)$ estimating the blur extent. We may now write the cross-correlation components, as

$$\begin{aligned} P_{r_p r_q}(i,j) &= E[r_p(m,n) r_q(m+i, n+j)] \\ &= \int_{\Re_p(\Theta)} \int_{\Re_q(\Theta)} h_p(\xi,\eta) h_q(\psi,\zeta) P_{s_p s_q}(i - \xi + \psi, j - \eta + \zeta) d\xi d\eta d\psi d\zeta \\ &\quad + \delta(i,j) \sigma_{v_p} \sigma_{v_q} \end{aligned} \tag{15}$$

is the cross-correlation function of the $P_{s_p s_q}(x,y) = E\{s_p(\xi,\eta) s_q(\xi + x, \eta + y)\}$ where . Then, taking the DFT of (15), we have $s(m,n)$ ideal continuous domain image

$$S_{r_p r_q}(k,l) = S_{s_p s_q}(k,l) H_p(k,l) H_q^*(k,l) + \sigma_{v_p} \sigma_{v_q} \tag{16}$$

, $P_{r_p r_q}(x,y)$ which denotes the samples of $P_{r_p r_q}(i,j)$ represents the DFT of $S_{r_p r_q}(k,l)$ where for the $h_p(x,y;\Theta)$ denotes the samples of the continuous Fourier transform of $H_p(k,l)$ and channel given by pth

(17) $$H_p(k,l) = \int_{\Re_p(\Theta)} h_p(x,y;\Theta)\exp\left(-j\frac{2\pi}{N}kx\right)\exp\left(-j\frac{2\pi}{N}ly\right)dxdy$$

Thus, the power spectrum for each channel reduces to

(18) $$S_{r_p r_p}(k,l) = S_{s_p s_p}(k,l)\left|H_p(k,l)\right|^2 + \sigma_{v_p}^2$$

The key point here is to incorporate the cross-spectral components and to include them in the , which can be obtained from $S_{s_p s_q}(k,l)$ computation of the power spectrum of the ideal image, the AR model of (1) as

(19) $$S_{s_p s_p}(k,l) = \frac{\sigma_{w_p}^2 + \sum_{q,q\neq p}\sum_{(m,n)} C^{pq}(m,n) S_{s_p s_q}(k,l)}{\left|1 - \sum_{(m,n)} C^{pp}(m,n)\right|^2}$$

are the DFT of the correlation coefficients computed using a least $C^{pq}(k,l)$ where squares procedure. For example, for the RGB color image, the power spectrum for the red channel is fully computed using the power spectrum of the red spectral component including the power spectra of the green and blue components. Now, we need to compute the derivative of the CLF for each channel as

(20) $$\frac{\partial}{\partial\theta_i}\mathrm{L}(\Theta|c_{i,j}(m,n),\sigma_{v\,i}^2,\sigma_{w_i}^2) = -\sum_k\sum_l\left\{\left(\frac{1}{S_{r_p r_p}(k,l)} - \frac{1}{N^2}\frac{\left|R_p(k,l)\right|^2}{S_{r_p r_p}^2(k,l)}\right)\frac{\partial}{\partial\theta_i}S_{r_p r_p}(k,l)\right\}$$

, can be $\frac{\partial}{\partial\theta_i}S_{r_p r_p}(k,l)$ Here, the derivative of the power spectrum component, computed depending on the particular parametric form of the unknown PSF. For example, for a uniform motion blur, [9,10]

(21) $$\frac{\partial}{\partial\theta_i}S_{r_p r_p}(k,l) = \frac{1}{a}\left\{-2\left|H_p(k,l)\right|^2 + \exp\left(j\frac{2\pi}{N}ka\right)H_p(k,l) + \exp\left(-j\frac{2\pi}{N}ka\right)H_p^*(k,l)\right\}S_{s_p s_p}(k,l)$$

for this form is given by $H_p(k,l)$ where

(22)

$$H_p(k,l) = \left(-j\frac{2\pi}{N}k\frac{a-1}{2}\right)\frac{\sin\frac{2\pi}{N}k\frac{a}{2}}{\frac{2\pi}{N}k\frac{a}{2}}$$

is given by $\frac{\partial}{\partial\theta_i}S_{r_p r_p}(k,l)$ Also, for the out-of-focus blur,

(23)

$$\frac{d}{d\theta}S_{r_p r_p}(k,l) = \left\{\frac{-4}{R}\left|H_p(k,l)\right|^2 + \frac{2}{R}J_0\left(\frac{2\pi}{N}R\sqrt{k^2+l^2}\right)\left(H_p(k,l)+H_p^*(k,l)\right)\right\}S_{s_p s_p}(k,l)$$

$H_p(k,l)$ where in this case

(24)

$$H(k,l) = NR\frac{J_1\left(\frac{2\pi}{N}R\sqrt{k^2+l^2}\right)}{\sqrt{k^2+l^2}}$$

2.2 Implementation of the ML Estimator

The multichannel estimation procedure can be described by the following algorithm:

for the different channels using least squares procedure $\sigma_{w_i}^2$ and $\{c^{pq}(m,n)\}$ 1) Estimate

from a uniform region in the different channels σ_v^2 2) Estimate

using (19) and employing the cross spectral components. $S_{s_p s_p}(k,l)$ 3) Compute

4) Use the parametric form of the specific PSF, namely uniform blur or out-of focus blur, and , to some initial values. Θ set the parameter,

DO UNTIL convergence criterion is satisfied

using (22) or (24) depending on the parametric form chosen. $\left|H_p(k,l)\right|^2$ 5) Compute

using (18). $S_{r_p r_p}(k,l)$, compute σ_v^2 6) Given

7) Compute the value of CLF using (12).

Compute the derivative of the CLF with respect to the unknown parameter using (8 (20) and either (21) or (23). Again depending on the parametric form chosen.

using a gradient based numerical optimization technique. Θ 9) Update

END UNTIL

3. EXPERIMENTAL RESULTS

Using the above described procedure for blur identification, several experiments were successfully conducted on color images that were blurred by uniform linear motion or out-of-focus blur. Here, we present the results uniform motion blur experiments that were conducted using the original color image of " TANK" as in Figure 1. We blurred this image by uniform =40 dB as shown in Figure 2. SNR =10 and additive noise equivalent to a motion blur of size The identified parameter was computed without cross spectral correlation (i.e. independent =7.5 for each channel. The blur extent a channels) and the blur extent estimated was about estimated by the above multichannel procedure, i.e. including the cross spectral components, =9. The restoration results using the estimated parameters of the two a was estimated as cases are shown in figures 3 and 4, respectively. We note here that we are dealing with PSF was computed a that is expressed as a function of one parameter. The identified parameter for each channel while including the cross-spectral components of the other channels.

Clearly, since the channels were blurred with the same PSF, we should expect the estimated to be the same in all channels. a extent

To test the performance of this method with noise, we blurred the " TANK " image with a =10 and separately added Gaussian noise that corresponds to a uniform motion blur of extent of 10, 20, 30, 40, and 50 dB. The blur extent we estimated using both the independent SNR identification method and the multichannel approach described here. The results are shown in Table1. We observe that the multichannel approach gives better results than the independent identification. Obviously, this improvement is due to the inclusion of the cross-spectral levels the improvement is moderate, the fact that cross-SNR components. Although at low spectral component incorporation produce better results is still valid.

4. CONCLUSION

To summarize, we may say that the novel approach outlined in this paper is very useful in identifying blur extents of uniform motion or out-of-focus degradations and can be used levels more than 20dB. This contribution is very important in the field SNR satisfactory for of image restoration since multichannel identification techniques are few and limited in performance.

Figure 2. The blurred "TANK" image with =10a uniform motion blur of extent

Figure 1. The original color "TANK" image.

Figure 4. The restored " TANK" image using =9 including a the identified parameter of the cross-spectral correlation.

Figure 3. The restored "TANK" image =7.5a using the identified parameter of without including the cross-spectral correlation

(Note: The images appear here in gray levels due to printing limitations. Full color images can be seen in the CD-ROM version of the proceedings)

Table 1. The identified blur extents for the TANK image that was degraded by uniform motion blur of size $a = 10$ at different noise levels. The independent blur identification and the multichannel blur identification refer to estimating the blur from each channel without and with cross-spectral components, respectively.

SNR (dB)	Independent blur identification			Multichannel blur identification		
	Channel R	Channel G	Channel B	Channel R	Channel G	Channel B
10	7.1	7	7.1	7.5	7.5	7.6
20	7.2	7.3	7.2	8.2	8.1	8.1
30	7.3	7.3	7.3	8.5	8.5	8.5
40	7.5	7.4	7.5	9	8.9	9
50	7.8	7.8	7.9	9.3	9.3	9.4

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