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Direct method for restoration of motion-blurred images

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We deal with the problem of restoration of images blurred by relative motion between the camera and the object of interest. This problem is common when the imaging system is in moving vehicles or held by human hands, and in robot vision. For correct restoration of the degraded image, it is useful to know the point-spread function (PSF) of the blurring system. We propose a straightforward method to restore motion-blurred images given only the blurred image itself. The method first identifies the PSF of the blur and then uses it to restore the blurred image. The blur identification here is based on the concept that image characteristics along the direction of motion are affected mostly by the blur and are different from the characteristics in other directions. By filtering the blurred image, we emphasize the PSF correlation properties at the expense of those of the original image. Experimental results for image restoration are presented for both synthetic and real motion blur. [S0740-3232(98)01406-9]

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1. INTRODUCTION

Image restoration methods can be considered as direct techniques when their results are produced in a simple one-step fashion.[1] Equivalently, indirect techniques can be considered as those in which restoration results are obtained after a number of iterations. Known restoration techniques such as inverse filtering and Wiener filtering[2,3] can be considered as simple direct restoration techniques. The problem with such methods is that they require a knowledge of the blur function [i.e., the point-spread function (PSF)], which is, unfortunately, usually not available when dealing with images blurred by motion.

The method proposed in this paper deals with applying direct image restoration techniques even though the blur function is unknown. Therefore it is concerned with direct identification of the blur function separate from and before the restoration operation. The quality and the reliability of the image restoration process is usually based on the accuracy of information concerning the degradation process.

For a given digital picture of the original scene $f(i, j)$, a common practical model[2,4] of the corresponding degraded picture $g(i, j)$ is

$$g(i, j) = \sum_m \sum_n h(i - m, j - n) f(m, n) + n(i, j), \tag{1}$$

where $h(i, j)$ is a linear shift-invariant PSF and $n(i, j)$ is random noise.

Early approaches for identification of the blur[2,4] involve methods in which identification is performed separately from the restoration process. These approaches are usually rather simple and include fewer computational requirements. A possible case for such approaches occurs when it is known *a priori* that a certain portion of the degraded picture is the image of a point, a line, or an edge in the original picture, but these cases are often not applicable to real-life images. The early method for blur identification,[5] where no specific knowledge about the original image was assumed, dealt with the case of uniform linear motion blur that is described by a square-pulse PSF and used its property of periodic zeros in the spectral domain of the blurred image. These zeros were emphasized in the spectral domain, and the blur extent was estimated by measuring the separations between these zeros. The assumption of zeros in the spectral domain is not satisfied in various cases of motion degradation such as accelerated motion[6,7] and low-frequency vibrations.[8]

More recent developments in blur identification[9–11] relate the identification process with the restoration process. These methods are more complicated and require more computations. Restoration results are criterion based, and blur parameters can be corrected until each criterion is satisfied. Therefore more types of blur can be considered. The success of these methods depends on the reliability of the original image model. Recent important developments are the maximum-likelihood image and blur identification methods. These methods model the original image, the blur, and the noise process. The original image is modeled as a two-dimensional autoregressive process, and the blur is modeled as a two-dimensional linear system with finite impulse response. A maximum-likelihood estimation is used for identification of the image and blur parameters. The identification of the blur model parameters is incorporated into the restoration algorithm and requires many computations. Another new blur identification method[12] uses an estimation of the original image power spectrum (an expected value). The PSF estimate is chosen from a collection of candidate PSF's to provide the best match between the restoration residual power spectrum and the expected residual spectrum given that the candidate PSF is the true PSF.

In this paper we propose a new method to estimate the blur function given only the motion-blurred image. Previous work,[13] summarized in Section 2, investigated the motion-blurring effects on an image and established the basic concepts with which blur characteristics such as direction and extent were extracted from the blurred image. Based on these concepts, a method to identify the blur function is proposed here. The identified function is then used to restore the blurred image by using a Wiener filter. The method addresses one-dimensional blur types, which are common in the case of motion degradation, and we assume the blur effect to be linear and space invariant and the original image to be a stationary random process. These assumptions are common when dealing with practical image restoration algorithms.[1,2,4]

2. IDENTIFICATION OF THE MOTION BLUR FUNCTION

The blur function needed for direct restoration of the blurred image can be completely described by the PSF or by the optical transfer function (OTF), which is the Fourier transform of the PSF. The OTF can be formulated as

$$\mathrm{OTF} = \mathrm{MTF} \exp(j\ \mathrm{PTF}), \tag{2}$$

where the modulation transfer function (MTF) is the absolute value of the OTF and the phase transfer function (PTF) is its angle.

The first step of the method is to identify the blur direction. Given the blur direction, correlation properties of the blur function are then identified. This is performed by filtering the blurred image so that correlation properties stemming from the original image are suppressed, and the filtered version is characterized mostly by the blur function correlation properties. This leads to identification of the blurring MTF. For causal blur the PTF can then be extracted directly from the MTF. Using the OTF, we then employ a simple Wiener filter to restore the blurred image. The method will be presented step by step in the following subsections. The formulation will be presented in Section 3.

A. Motion Blur Phenomena

As a result of relative motion between the camera and the object of interest, adjacent points in the image plane are exposed to the same point in the object plane during the exposure time. The intensity of an image of an original point is shared between these image plane points according to the relative duration in which each point is exposed to light from the original point. The smearing tracks of the points determine the PSF in the blurred image. Contrary to other blur causes such as atmospheric or out-of-focus effects, motion blur is usually considered as one dimensional, since during exposure time that is relatively short (in real-time imaging, approximately 1/30 s), motion direction does not change. This smearing effect in the motion direction acts as a low-pass filter in the spatial-frequency domain.

B. Identification of the Blur Direction

The first necessary step of the method should be identification of the motion direction relative to the image axis. Extensive studies of image power spectra show that an excellent simple model for imagery statistics is that of a spatially isotropic first-order Markov process.[1] Hence the autocorrelation of the original image and its power spectrum are assumed to be approximately isotropic. As a consequence of motion, image resolution is decreased mostly in the motion direction. Therefore implementation of a high-pass filter (such as a simple image derivative) to the blurred image in this direction should suppress more of the image intensity than implementing it in other directions. Therefore motion direction is identified by measuring the direction where the power spectrum of the image derivative is lower.

C. Decorrelating Real Images

Real images are characterized by high spatial correlation. A simple decorrelation (whitening) filter can be a derivative operation. This operation in a digital image is approximately a differentiating operation whereby each pixel in the filtered image is the difference between two adjacent pixels in the original image. This operation has been found to be an effective decorrelating filter.

D. Extracting Motion Blur Correlation Properties

The effect of motion blur on real images was analyzed in detail in Ref. 13. Since the motion blur is usually one dimensional, its effect varies according to the direction in the blurred image relative to the motion direction. Since the PSF is varying in the motion direction, it is not correlated perpendicularly to the motion direction. Therefore a whitening filter implemented perpendicularly to the motion direction (i.e., a filter that is not varying in the motion direction) will not affect the PSF correlation properties. However, such a filter will significantly suppress correlation properties stemming from the original image, which is highly correlated in all directions. On the other hand, implementation of a whitening filter in the motion direction will have a different effect. The PSF has the same effect on all the image points. The points of the original image will become PSF patterns that merge into each other, forming the blurred image. A whitening derivative filter in this direction will form patterns similar to that of the PSF derivative. Such a filter implemented in both directions will form such patterns surrounded by extremely suppressed decorrelated regions. Therefore these patterns can be evaluated by performing an autocorrelation operation on the blurred image derivative. Since these patterns are in the motion direction, the autocorrelation should be performed in this direction. Implementing the autocorrelation function (ACF) to all the image derivative lines in the motion direction, and then averaging them,[14] will suppress the noise stimulated by the whitening operations. Furthermore, such averag-

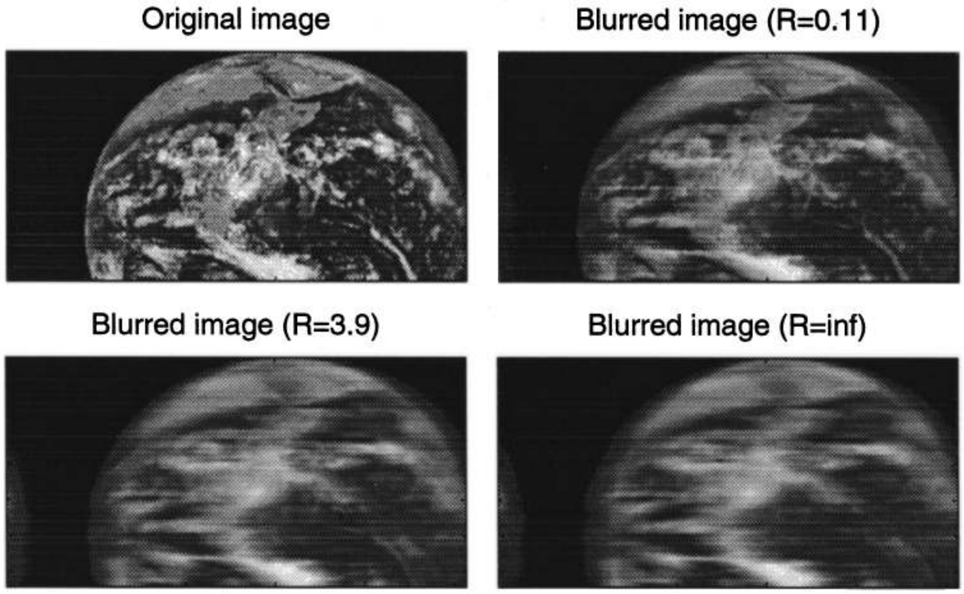

Fig. 1. Image of the Earth horizontally blurred by accelerated motion with 20-pixel blur extent and different values of R.

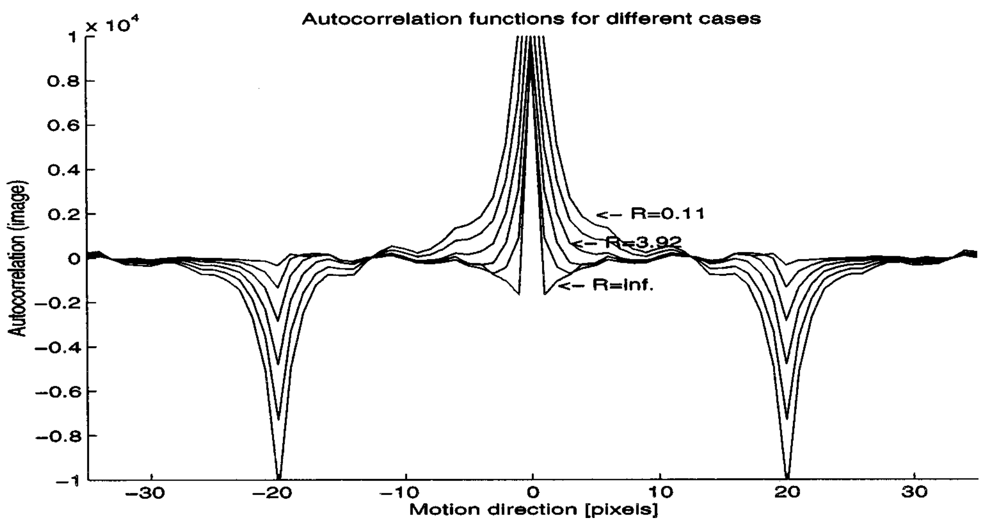

Fig. 2. Average of the autocorrelation functions of the blurred Earth image derivative lines in the motion direction for different values of R.

ing will cause cancellation of correlation properties left over from the original image, which can be different from one line to another. This is especially true since the assumption of stationarity of the original image is often not a very good one.

The final conclusion here is that the average of the ACF's of the blurred image derivative lines in the motion direction is similar to the ACF of the PSF derivative.

E. Identification of the Motion Function

The average spectral density of the image derivative lines (in the motion direction) can be obtained by Fourier-transforming the averaged ACF. Given the similarity concluded in Subsection 2D, the shape of this spectral density should be similar to that of the PSF derivative power spectrum. Dividing it by the power spectrum of the derivative filter (performed in the motion direction) will yield the power spectrum of the PSF itself. The whitening filter performed perpendicularly to the motion direction is not considered here, since it does not affect the PSF correlation properties as discussed in Subsection 2.D. The MTF of the blur is then the square root of its power spectrum. If the blur is causal, the PTF can be straightforwardly extracted from the MTF by using the Hilbert transform as described in Section 3. The motion function (OTF) is then obtained from Eq. (2).

The reliability of the blur function estimate depends on the success of the original image whitening operation. When the whitening is imperfect, the ACF of the PSF derivative will be also influenced by the correlation properties of the original image. In this case the image derivative will have more low-frequency content stemming from the original image, and therefore the identified ACF will usually have higher values close to its center. The identified MTF will then show more modulation transfer at the lower frequencies.

3. FORMULATION OF THE METHOD

A discrete derivative of the blurred image $f(i, j)$, where i and j are the horizontal and vertical directions, respectively, can be approximated, for example, by[13]

$$[\Delta f(i, j)]_{k^\circ} = f(i, j) * d(i, j),$$

$$d(i, j) = \begin{bmatrix} -1 & 1 - \tan(k) \\ 0 & \tan(k) \end{bmatrix} \tag{3}$$

for $0 \geqslant k \geqslant -45°$ relative to the positive horizontal direction, where $*$ is the convolution operator.

The motion direction is identified by employing a simple high-pass filter such as a derivative operation [Eq. (3)] in all the directions and measuring the total intensity in each direction. The motion direction will then be the direction in which the total intensity is the lowest. The total intensity of the image derivative $I(\Delta g)$ in direction k is

$$[I(\Delta g)]_{k^\circ} = \left| \sum_{1}^{N-1} \sum_{1}^{M-1} [\Delta g(i, j)]_{k^\circ} \right|, \tag{4}$$

where M and N are the number of rows and columns, respectively, in the image derivative $\Delta g(i, j)$.

A digital ACF of each image derivative line in the motion direction is then performed, and the average of the ACF's of these lines, $\bar{R}_{\Delta f}$, is calculated.

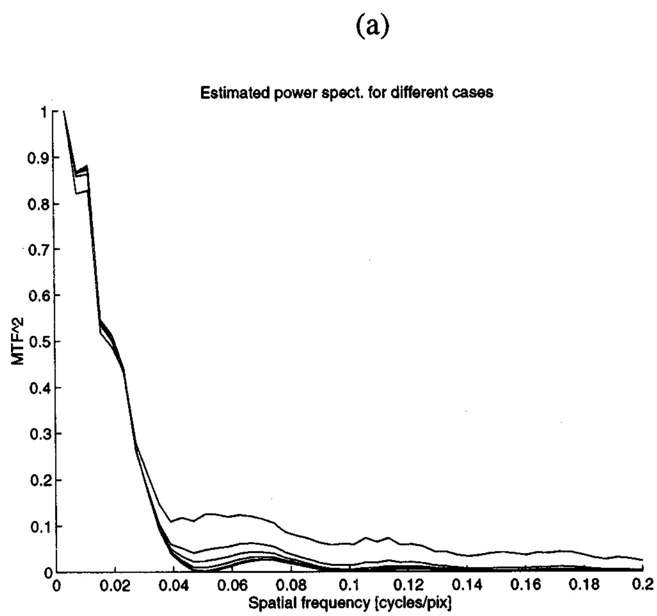

Fig. 3. Comparison of the identified and true power spectra of acceleration motion blur PSF's: (a) identified power spectra obtained by Fourier-transforming the ACF's of Fig. 2, (b) true power spectra.

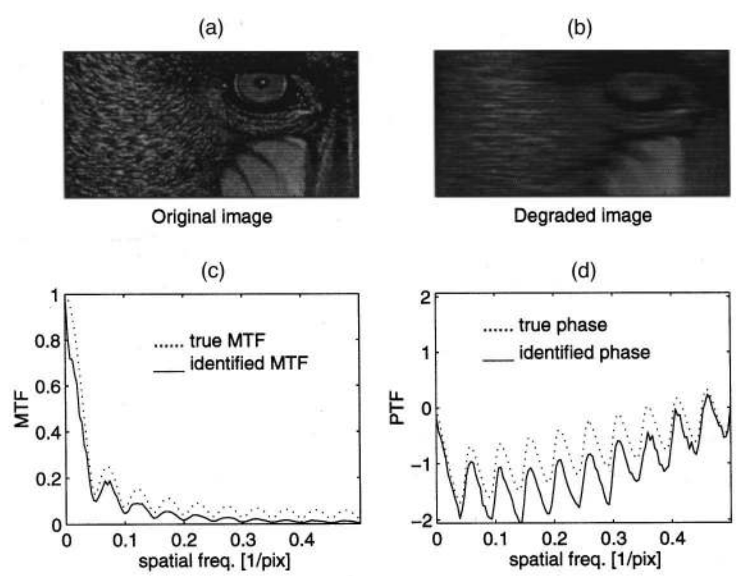

Fig. 4. Blur function identification: (a) original image, (b) image blurred by accelerated motion with $R = 10$ and 20-pixel blur extent, (c) true versus identified MTF, (d) true versus identified phase.

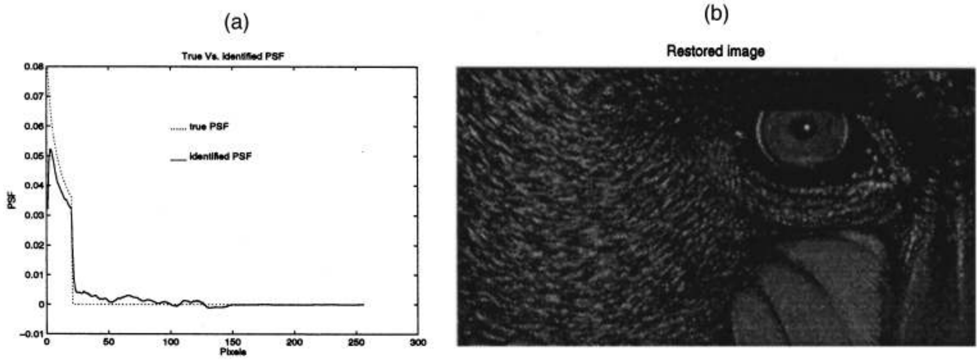

Fig. 5. (a) True versus identified PSF, (b) restored image with use of the identified OTF.

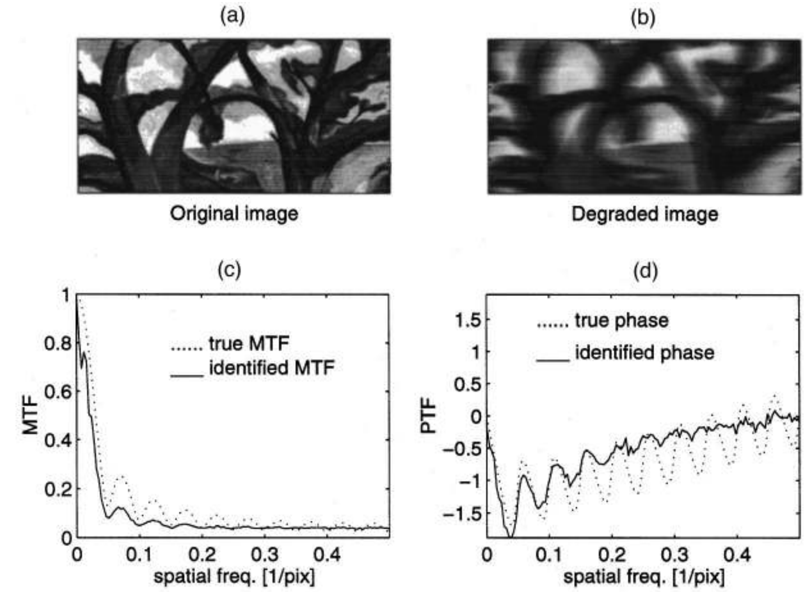

Fig. 6. Blur function identification from a noisy blurred image: (a) original image, (b) image blurred by accelerated motion with $R = 10$ and 20-pixel blur extent and an additive noise forming a 30-dB signal-to-noise ratio, (c) true versus identified MTF, (d) true versus identified phase.

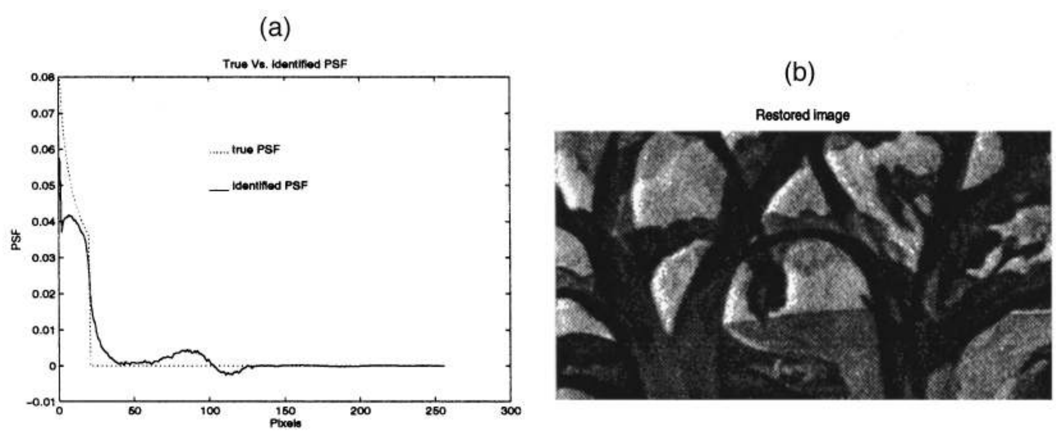

Fig. 7. (a) True versus identified PSF, (b) restored image with use of the identified OTF.

An ACF $R_l(j)$ of an M-pixel image line l is defined as

$$R_l(j) = \sum_{i=-M}^{M} l(i+j)l(i), \qquad \text{integer } j \in [-M, M], \tag{5}$$

where $l(i) = 0$ for $i \notin [0, M]$. The computation of the digital ACF's in the motion direction k (relative to the positive horizontal direction) is performed by rotating the image itself $-k°$ with use of the two-dimensional interpolation technique and then performing the autocorrelation operation [Eq. (5)] on the horizontal lines of the rotated image. The commonly used bilinear interpolation technique[15] was employed to estimate the rotated image. In this technique the interpolated pixel is a combination of the values of the four closest pixels according to the rotation transform.

Since the average ACF of the image derivative lines, $\bar{R}_{\Delta f}$, resembles the ACF of the PSF derivative, its discrete Fourier transform $\bar{S}_{\Delta f}$ will resemble the power spectrum of the PSF derivative S_{dPSF}:

$$\bar{S}_{\Delta f}(u) \approx S_{\mathrm{dPSF}}(u), \tag{6}$$

where

$$S_{\mathrm{dPSF}}(u) = |\mathrm{OTF}(u)D(u)|^2, \tag{7}$$

where D is the Fourier transform of the derivative approximation. The MTF of the degradation process is the absolute value of the OTF and can be approximated from Eq. (7) and the following:

$$\mathrm{MTF}(u) \approx \sqrt{\bar{S}_{\Delta f}(u)}/|D(u)|. \tag{8}$$

For various PSF types usually referred to as minimum phase functions, the magnitude and the phase of the OTF are related by the Hilbert transform.[16–18] Under the conditions that the PSF of the blur is real, causal, and stable,

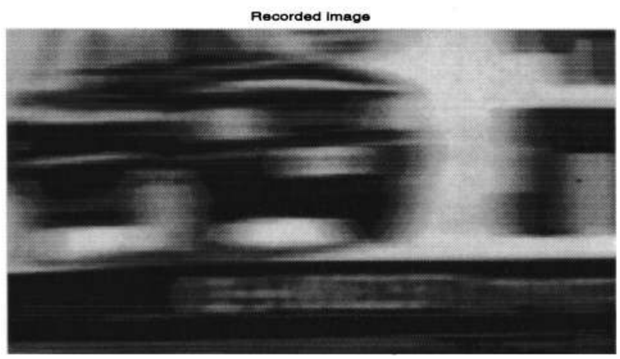

Fig. 8. Picture taken from a moving car.

the log MTF and the PTF will be Hilbert transforms of each other. The PTF will then be extracted from the MTF by

$$\mathrm{PTF}(u) = -\frac{1}{2\pi}\int_0^{2\pi} \ln[\mathrm{MTF}(\alpha)]\cot\left(\frac{u-\alpha}{2}\right)\mathrm{d}\alpha. \tag{9}$$

The OTF used to restore the blurred image is then obtained from Eq. (2).

The minimum-phase conditions are usable in many situations.[16] General usage concerns digital filters that are often specified in terms of the magnitude of the frequency response. In such cases the phase response cannot be chosen arbitrarily if a stable and causal system is desired.

4. ANALYSIS FOR ACCELERATED MOTION

Accelerated motion is an example that represents a variety of motion PSF types, depending on the acceleration and the initial velocity. The line spread function (LSF) of accelerated motion is[6]

$$\mathrm{LSF}(x) = \frac{1}{t_e({\nu_0}^2 + 2ax)^{1/2}}, \tag{10}$$

where a is the acceleration, ν_0 is the initial velocity, and t_e is the exposure time. The accelerated motion parameter

$$R = {\nu_0}^2/a \tag{11}$$

describes the smoothness of the motion during the exposure. R is proportional to the relative homogeneity of the PSF as defined and discussed in Ref. 13. In Fig. 1 the image of the Earth was blurred by accelerated motion with different values of R. We can see that for the same blur extent, as R increases, the blur effect is severer. When R is infinity, the motion is of a uniform velocity type and the blurring effect is maximal. Figure 2 shows the average of the ACF's of the image derivative lines in the motion direction for different values of R varying from infinity to 0.11. The extent of the blur can be identified

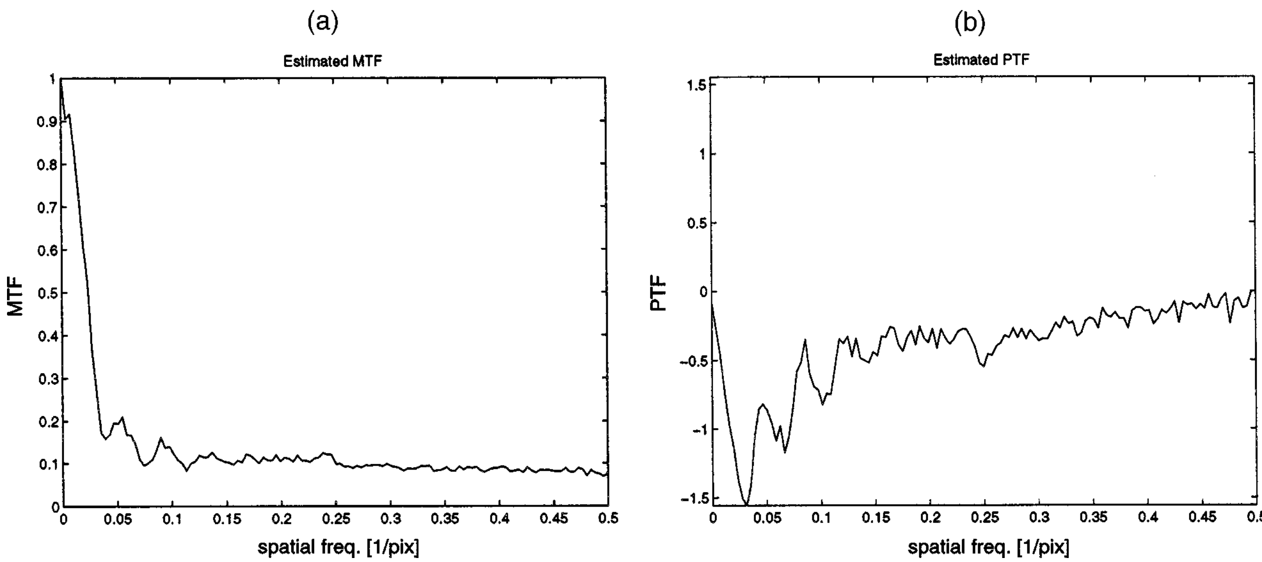

Fig. 9. (a) Identified MTF of the motion blur, (b) identified PTF of the motion blur.

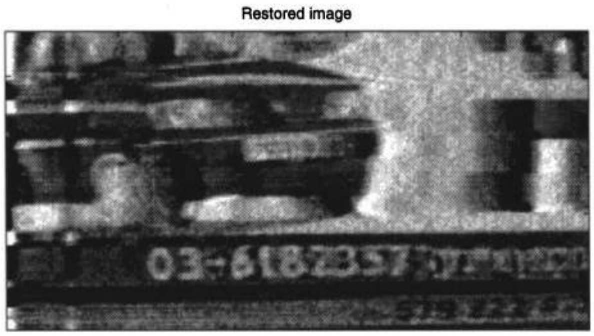

Fig. 10. Restored image with use of the identified OTF.

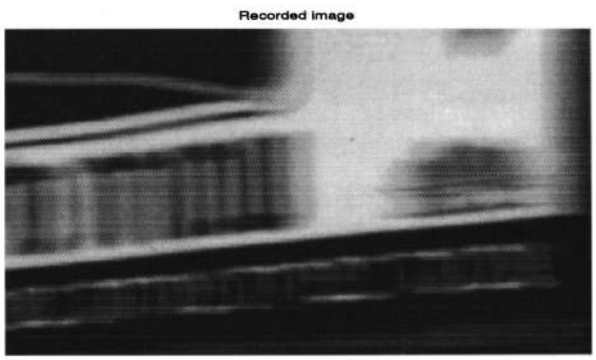

Fig. 11. Picture taken from a moving car.

according to the distance between the global minimum of the function and its center $[\bar{R}_{\Delta f}(0)]$. The capability of the blur extent identification was analyzed quantitatively in Ref. 13.

Figure 3 shows a comparison of the estimated and true power spectra. The estimated power spectra are the Fourier transforms of the ACF's of the blurred Earth image derivative appearing in Fig. 2. We can see that even for $R = 0.11$, where the blur extent was not identified, the estimated power spectrum resembles the true one.

5. RESULTS OF BLUR IDENTIFICATION AND IMAGE RESTORATION

Results of implementation of the method are presented here for both synthetic and true motion blurs. The application of synthetic blur is presented in Subsection 5.A. It enables us to compare the true degrading function with the identified one, and it also show the effects of image restoration. A real-life motion blur example is presented in Subsection 5.B.

A. Results for Synthetic Blurring

The blurred image of Fig. 4(b) is obtained by blurring the original image of Fig. 4(a) with the use of a uniform motion function of 20-pixel blur extent. The MTF shown in Fig. 4(c) was identified by the algorithm formulated in Section 3. The identified PTF shown in Fig. 4(d) was then calculated by using Eq. (9).

Good similarities between the true and the identified MTF's and PTF's determining the blur are presented in Figs. 4(c) and 4(d), respectively. The identified PSF presented in Fig. 5(a) was obtained by Fourier-transforming the OTF constructed from the identified MTF and PTF according to Eq. (2). The restored image with use of the identified blur function with a Wiener filter[2,3] is presented in Fig. 5(b). Figure 6 concerns a noisy blurred image. The original image here was blurred according to Eq. (2) by a uniform motion function of 20-pixel blur extent and additive noise forming a 30-dB signal to-noise ratio. The similarities between the true and the identified MTF's and PTF's are presented in Figs. 6(c) and 6(d), respectively. We can see that here the capability of the phase identification decreases at higher spatial frequencies as a result of the noise. A comparison of the true and the identified PSF's is presented in Fig. 7(a). The restored image is shown in Fig. 7(b).

B. Results for Real-Life Motion Blur

Figure 8 shows an image of a commercial sign taken from a moving car. The identified MTF presented in Fig. 9(a) was estimated by using the algorithm formulated in Section 3. The PTF of the blur presented in Fig. 9(b) was calculated from the estimated MTF by using Eq. (9). The restored image with use of the identified OTF with a Wiener filter is presented in Fig. 10. We can clearly read the phone number, which is extremely blurred and cannot

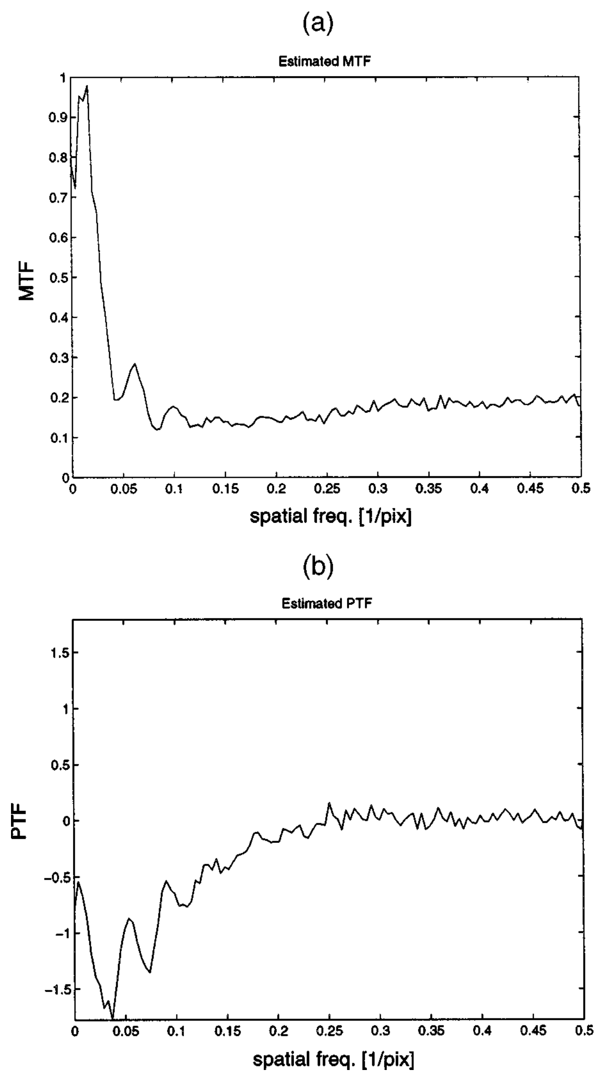

Fig. 12. (a) Identified MTF, (b) identified PTF.

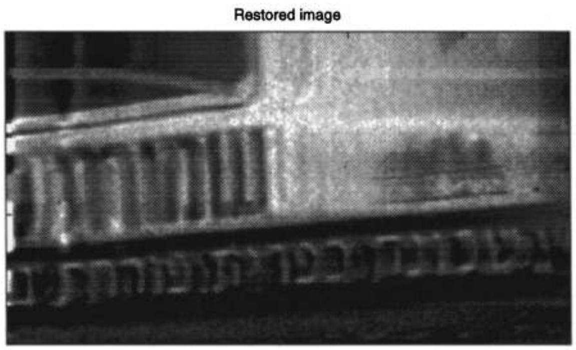

Fig. 13. Restored image with use of the identified OTF.

be read in the recorded image. Another number (that we could not know exists) can be read in the restored image at the bottom. The image of Fig. 11 was also taken from a moving car. The MTF and the PTF identified by the proposed algorithm are presented in Figs. 12(a) and 12(b), respectively. The restored image is presented in Fig. 13. Here we can also read the Hebrew words ("blossoming rustic neighborhood"), which cannot be read in the recorded image.

6. SUMMARY AND CONCLUSIONS

A direct method for motion-blurred image restoration is presented. The method first identifies the function of the blur and then uses it to restore the blurred image with a standard restoration filter. The blur identification is performed by filtering the blurred image so that the correlation properties of the filtered image are characterized mostly by the blur function. Examples such as accelerated motion and imaging from a moving car are presented. Good blur identification and image restoration are achieved. Considering that no knowledge is assumed here about the original image and about the motion type (except that it is one dimensional), this method can be compared with Cannon's direct method.[5] Contrary to Cannon's approach, the method here does not assume uniform (or almost-uniform) motion. Furthermore, a complete estimation of the blur function is extracted here from the blurred image, where in Cannon's method only the blur extent and direction are estimated from the blurred image.

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REFERENCES

1. M. P. Ekstrom, ed., *Digital Image Processing Techniques* (Academic, Orlando, Fla., 1984).
2. A. Rosenfeld and A. C. Kak, *Digital Picture Processing* (Academic, New York, 1982), Vol. 2.
3. H. Lim, K. C. Tan, and B. T. G. Tan, "Edge errors in inverse and Wiener filter restorations of motion-blurred images and their windowing treatment," CVGIP: Graph. Models Image Process. **53**, 186–195 (1991).
4. A. K. Jain, *Fundamentals of Digital Image Processing* (Prentice-Hall, Englewood Cliffs, N.J., 1989).
5. M. Cannon, "Blind deconvolution of spatially invariant image blurs with phase," IEEE Trans. Acoust. Speech Signal Process. **ASSP-24**, 58–63 (1976).
6. S. C. Som, "Analysis of the effect of linear smear on photographic images," J. Opt. Soc. Am. **61**, 859–864 (1971).
7. O. Hadar, S. R. Rotman, and N. S. Kopeika, "Target acquisition modeling of forward-motion considerations for airborne reconnaissance over hostile territory," Opt. Eng. **33**, 3106–3117 (1994).
8. O. Hadar, I. Dror, and N. S. Kopeika, "Image resolution limits resulting from mechanical vibrations. Part IV: real-time numerical calculation of optical transfer function and experimental verification," Opt. Eng. **33**, 566–578 (1994).
9. A. K. Katsaggelos, ed., *Digital Image Restoration* (Springer-Verlag, New York, 1991).
10. R. L. Lagendijk, A. M. Tekalp, and J. Biemond, "Maximum likelihood image and blur identification: a unifying approach," Opt. Eng. **29**, 422–435 (1990).
11. G. Pavlovic and A. M. Tekalp, "Maximum likelihood parametric blur identification based on a continuous spatial domain model," IEEE Trans. Image Process. **1**, 496–504 (1992).
12. A. E. Savakis and H. J. Trussell, "Blur identification by residual spectral matching," IEEE Trans. Image Process. **2**, 141–151 (1993).
13. Y. Yitzhaky and N. S. Kopeika, "Identification of blur parameters from motion blurred images," CVGIP: Graph. Models Image Process. **59**, 310–320 (1997).
14. D. F. Mix and J. G. Sheppard, "Average correlation functions in on-line testing of linear systems," IEEE Trans. Aerosp. Electron. Syst. **AES-9**, 665–669 (1973).
15. R. J. Schalkoff, *Digital Image Processing and Computer Vision* (Wiley, New York, 1989).
16. A. V. Oppenheim and R. W. Schafer, *Digital Signal Processing* (Prentice-Hall, Englewood Cliffs, N.J., 1975), Chap. 7.
17. B. Gold and C. M. Rader, *Digital Processing of Signals* (McGraw-Hill, New York, 1969).
18. M. Bellanger, *Digital Processing of Signals* (Wiley, New York, 1984).