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Motion blur parameters estimation for image restoration

Ratnakar Dash*, Banshidhar Majhi

CSE Department, NIT Rourkela, Rourkela, India

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ABSTRACT

This paper deals with estimation of parameters for motion blurred images. The objectives are to estimate the length (L) and the blur angle (θ) of the given degraded image as accurately as possible so that the restoration performance can be optimised. Gabor filter is utilized to estimate the blur angle whereas a trained radial basis function neural network (RBFNN) estimates the blur length. Once these parameters are estimated the conventional restoration is performed. To validate the proposed scheme, simulation has been carried out on standard images as well as in real images subjected to different blur angles and lengths. The robustness of the scheme is also validated in noise situations of different strengths. In all situations, the results have been compared with standard schemes. It is in general observed that the proposed scheme outperforms its counterparts in terms of restoration parameters and visual quality.

1. Introduction

The goal of image restoration is to reconstruct an approximated version of the original image from a degraded observation. Image degradation occurs due to various reasons like camera mis-focus, atmospheric turbulence, camera or object motion, etc. The blurring in images due to motion is commonly encountered when there is a relative motion between the camera and object. Motion deblurring is required in many applications such as satellite imaging, medical imaging and traffic control. The motion may be linear or non-linear. The degradation due to motion can be modelled as a two dimensional linear shift invariant process. In many applications, the observed image $g(x, y)$ can be expressed as a two-dimensional convolution of the original image with the degradation function $h(x, y)$, and is expressed as,

$$g(x, y) = f(x, y) * h(x, y) + \eta(x, y). \tag{1}$$

where $*$ denotes the two dimensional linear convolution and $\eta(x, y)$ is the additive noise [1,2]. The degradation function $h(x, y)$ is also known as Point Spread Function (PSF). The degradation model (1) can otherwise be expressed in frequency domain as,

$$G(u, v) = F(u, v)H(u, v) + N(u, v) \tag{2}$$

where $G(u, v)$, $F(u, v)$, $H(u, v)$, and $N(u, v)$ are the frequency responses of the observed image, original image, PSF and noise respectively. In the absence of noise the above expression reduces to,

$$G(u, v) = F(u, v)H(u, v) \tag{3}$$

In classical restoration techniques, it is assumed that the PSF is known prior to restoration. So the restoration technique is just to inverse the process using frequency domain techniques with some regularization to avoid the noise amplification.

There exists a variety of schemes, which describes the deblurring techniques such as Wiener filter [2], Fourier wavelet regularized deconvolution [3], Expectation–Maximization algorithm for wavelet-based image deconvolution [4]. All these techniques have some apriori knowledge about the nature of the degradation function. In most of the practical situations, the degradation function $h(x, y)$ is not known. This makes the restoration process difficult to recover the original image only from the observed image. Such restoration is commonly known as blind deconvolution. This paper deals with restoration of linear motion blurred images. Motion blur parameter estimation problem can be classified into two categories. In the first category, parameters are estimated using multiple images [5,6]. The second category of algorithms estimate motion blur parameters using only a single image [7–9]. Our work falls in the second category, where blur parameters are determined from a single blurred image. Several researchers have proposed methods [10–13] to determine the motion blur parameters. In [12], Hough transform has been used to detect the lines in the spectrum of the blurred image and subsequently, bispectrum has been used to determine the blur parameters [14]. Authors in [11] developed an adaptive Adaline network to estimate motion length of a degraded image. This algorithm needs a rough estimation of motion length, which is achieved using power spectrum. In a recent work,

* Corresponding author.
E-mail address: ratnakar.dash@gmail.com (R. Dash).

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Igor Aizenberg and his team [10] developed a method to identify blur. However, their work is concentrated mostly on horizontal blur. The present work is a similar such attempt to estimate the motion blur parameters (theta, L) from degraded images apriori and subsequently utilize these parameters to reconstruct the PSF for restoration. Even though there is a large volume of work related to motion blur reported in the literature, researchers are still active in this direction to improve the results in terms of visual quality and peak signal to noise ratio (PSNR).

Here, Gabor filter and radial basis function neural network have been employed to determine motion blur parameters. After motion blur parameter estimation image is restored using classical restoration technique, namely Wiener filter [2]. The estimation strategy is also studied under noisy situations to test the robustness of the proposed scheme.

The rest of the paper is organised as follows. The blur model is described in Section 2. Blur angle estimation using Gabor filter is presented in Section 3. Section 4 describes the proposed method to determine the blur length. Noise robustness of the proposed scheme is outlined in Section 5. Section 6 deals with simulation and comparative analysis of the suggested scheme. Finally, Section 7 gives the concluding remarks.

2. Motion blur model

The Point Spread Function for motion blur can be described as

$$h(x,y)=\begin{cases}1/L & \text{if}\sqrt{x^2+y^2}\le L/2,\\ & y/x=\tan\theta\\ 0 & \text{otherwise}\end{cases} \quad (4)$$

Two parameters govern the motion blur: length of blur L and angle of blur θ. The restoration performance depends on the estimation of PSF, which in turn dependent on L and θ. So challenge lies for accurate estimation of these parameters from a given motion blurred image.

The proposed algorithm estimates the parameters θ and L separately. The PSF is constructed from the parameters and the conventional Wiener filter is used for restoration of the blurred image. The overall algorithm is described in Algorithm 1.

Algorithm 1.
Input: Motion blurred image
Output: Restored image
Step 1. The blur angle (θ) is determined using Gabor filter.
Step 2. The blurred image is rotated in the direction opposite to the blur angle to obtain the equivalent horizontal blurred image.
Step 3. The blur length (L) is estimated using RBFNN.
Step 4. PSF is constructed using the estimated blur parameters.
Step 5. The image is restored using the Wiener filter.

A detail of the parameter estimation is described in sequel in the following sections.

3. Angle estimation using Gabor filter

One of the important observation in motion blurred images is that its frequency spectrum shows dominant parallel lines which correspond to the angle of blur. This can be observed from the *Lena* image blurred with an angle theta = 30° and L = 20 shown in Fig. 1. So, any of the line detection algorithms can be used to determine the orientation of the parallel lines.

Gabor filters are Gaussian filters modulated by a sinusoidal wave. A good number of researchers have used Gabor filter bank to extract image features in applications like pattern recognition, image segmentation, etc. [15]. The function for a typical two-dimensional Gabor filter is defined as,

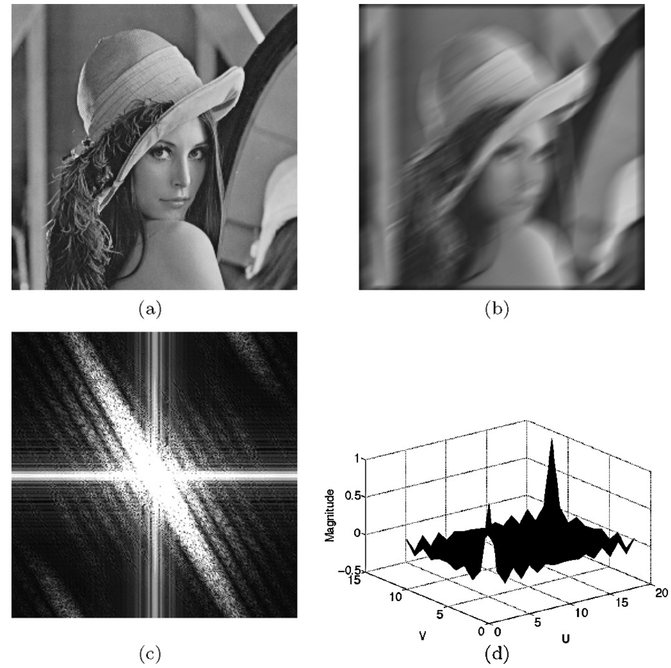

Fig. 1. (a) Original *Lena* image, (b) blurred *Lena* image with L = 20 and θ = 30°, (c) spectrum of the blurred *Lena* image and (d) frequency plot of PSF.

$$G(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right]\times\exp\left[-j\omega(x\cos\phi+y\sin\phi)\right] \quad (5)$$

where σ_x, σ_y is the standard deviation in x and y direction respectively. ϕ and ω represents the orientation and frequency of the Gabor filter. Modulated Gaussian filters can be used to find the orientation in the patterns. The two-dimensional Gabor filter masks for different orientation are shown in Fig. 2. In this plot, mask size of 7 × 7 has been used. The response of the Gabor filter varies with orientation parameter. This orientation parameter of a two dimensional Gabor filter has been utilized to calculate the blur angle. The two dimensional Gabor filter is convolved with the spectrum of the blurred image to get the response at different orientation by keeping other parameters fixed. The σ and ω values are chosen through experimentation and kept 3 and 1.75 respectively. The detail of the angle estimation strategy is described below.

Pattern of the frequency response of the blurred image has been used to find the motion direction. As it can be clearly seen from the Fig. 1(d), for a blur angle θ the patterns are oriented at $\alpha = \theta + 90$. So, the orientation of the lines in the spectrum of the blurred image is

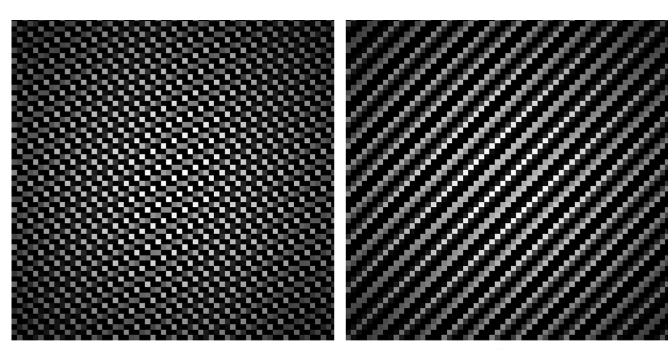

Fig. 2. (a) Gabor filter mask with ϕ = 30°, (b) Gabor filter mask with ϕ = 45°.