A Blind Restoration Approach for Defocused Barcode Images

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ABSTRACT

Use of a mobile camera for barcode decoding provides high portability and availability but it requires that the recorded barcode image must be accurate representation of the barcode that is available on the product. Barcode scanning is challenging because images may be degraded due to out-of-focus blur at the time of image acquisition. Therefore, image restoration is essential in making image sharp and useful. In case of blind restoration of such barcode images accurate estimation of out-of-focus blur parameter is highly desirable. In this article, a robust method has been proposed for estimating the radius of out-of-focus blur. Finite discrete ridgelet transform has been used to find the features of the blurred image and a radial basis function neural network is utilized to estimate the radius of out-of-focus blur. The experimental results reveal that proposed method more robust than the existing methods.

KEYWORDS

Blind Image Restoration, Finite Discrete Ridgelet Transform, Out-of-Focus Blur, Radial Basis Neural Network

1. INTRODUCTION

These days, almost all products in the market are utilizing a barcode technology. Barcode scanning with dedicated scanners is an established technology. Recently, the ease of use of cell phones with digital camera facility delivers a handy way for decoding barcode without make use of the traditional laser scanner which has poor portability. Camera phones can get an image of the barcode and later, it can transfer decoded information to a consumer product server to get product details (Gallo & Manduchi, 2011). The application of a camera phone in this area is thrilling if the captured image suffers with some type of degradation. Image blurring is often an issue that affects the performance of a bar code identification system. The out-of-focus (defocus) blur is appeared because of the inaccurate focal length adjustment. Image restoration methods (Tiwari, 2017; Tiwari, Shukla, Biradar, & Singh, 2014) available in the literature can be classified as blind deconvolution, where the blur kernel is not known and non-blind deconvolution, where the blur kernel is known. The first and foremost step in any blind image restoration technique is blur estimation. Numerous methods have been presented during the last decades, which attempt to estimate Point Spread Function (PSF) of blur concurrently with the image deconvolution (Kundur & Hatzinakos, 1996; Cannon, 1976). However, a number of efficient methods have suggested that blind deconvolution can be handled better with separate PSF estimation and after that non-blind deconvolution can be used as the consequent step (Gennery, 1973; Hummel, K. Zucker, and S. Zucker, 1987; Lane and R. Bates, 1987; Tekalp, Kaufman, & Wood, 1986). The work presented in this paper falls in the former category where PSF parameters are estimated before image deconvolution.

DOI: 10.4018/IJSITA.2017070103
Bhaskar et al. (1994) used Line Spread Function (LSF) information to estimate out-of-focus blur. They applied the power spectrum equalization (PSE) restoration filter for image restoration. However, this approach works only for modest areas of frequency. Shiqian et al. (2005) offered a method, which analyzes LSF to locate the perfect location of blur edges in spatial domain, and then applied this information for out-of-focus blur radius estimation. However, in presence of noise this algorithm gives poor results because it is challenging to find exact location of edges in noisy images. Sang et al. (1998) proposed a digital auto focusing system that applies block-based edge classification to decide the extent of out-of-focus blur. Due the fact that this approach works for the low and median frequencies, it fails for restoration of sharp details. Few methods transform image from spatial domain to frequency domain. Vivirito et al. (2002) used extended Discrete Cosine Transform (DCT) of Bayer patterns to extract edge details and applied this information to find out-of-focus blur amount. Gokstop (1994) computed image depth for out-of-focus blur estimation in his work. Though, this method needs two images of same scene from different angles to estimate depth. Moghadam (2008) advised an iterative procedure using Optical Transfer Function (OTF) estimate blur radius. However, this method is noise independent, but it needs manually adjustment of some parameters. Some other methods presented in Jiang et al. (2005) Su et al., (2008) Lee et al. (2010) and Chen et al. (2012) have used wavelet coefficients as features to train and test the Radial Basis Function (RBF) or cellular neural network for parameter estimation. All these approaches suffer with generalization capability. Authors tested the work with very few numbers of images with using wavelet as a feature extraction tool. The wavelet coefficients comprise distribution of energy along the frequency axis over the scale and horizontal, vertical and diagonal orientations of a detail image only therefore a large amount of the significant information has been lost by iteratively low-pass filtering. This paper suggests a multi-resolution-based features for blur radius estimation. The paper is organized into seven sections as follows. The image restoration model is discussed in Section 2. An overview of finite discrete ridgelet transform and radial basis function neural network is given in Section 3 and Section 4 respectively. The proposed methodology has been discussed in Section 5. Experimental results of blur radius estimation method are given in Section 6. Section 7 applies the deconvolution algorithm after blur radius estimation. At the last, conclusions and future work are discussed in Section 8.

2. IMAGE RESTORATION MODEL

Image restoration is used to restore the degraded image to an original image. The relationship between the input image \( f(x, y) \) and the estimated (restored) image \( g(x, y) \) is given by Tiwari (2017) and Tiwari et al. (2014):

\[
g(x, y) = f(x, y) * h(x - x', y - y') \, dx \, dy' + \eta(x, y) \quad (1)
\]

Here \( h(x - x', y - y') \) is the PSF \( \eta(x, y) \) is an additive noise. In discrete domain this equation is given by

\[
g(x, y) = f(x, y) * h(x, y) + \eta(x, y) \quad (2)
\]

whereas, in frequency domain, Equation (1) is

\[
G(u, v) = F(u, v) \, H(u, v) + N(u, v) \quad (3)
\]
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