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HPL-2010-168

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quality assurance, blur estimation, structured printing, functional imaging, barcodes

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External Posting Date: October 21, 2010 [Fulltext] Approved for External Publication

Internal Posting Date: October 21, 2010 [Fulltext]

Presented at IEEE International Conference on Image Processing, Hong Kong, China, September 26-29, 2010

BARCODE-BASED CALIBRATION OF A 1-D BLUR RESTORATION PIPELINE

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ABSTRACT

In high-speed printed media inspection environments, image restoration pipelines play a critical role in establishing and continually evaluating performance. A key role of such systems is to understand, mitigate (and possibly remove) artifacts introduced by motion blur. An approach is proposed that uses barcodes to help calibrate a one-dimensional blur restoration pipeline. Techniques are demonstrated whereby the structure of barcode markings may be leveraged to estimate motion blur parameters, even under extreme blur conditions or when the barcode is unknown. In addition, a framework for comparing blur estimation procedures based on barcode readability is introduced. These techniques can be applied independently of one another, but together form a set of useful tools for blur restoration pipeline calibration. Within this framework, it is shown that a low-complexity blur estimation strategy demonstrates performance competitive with state-of-the-art approaches in term of speed and accuracy.

Index Terms— Quality assurance, blur estimation, structured printing, functional imaging, barcodes.

1. INTRODUCTION

High-speed inspection environments include any system where a capture device is used to image moving items. A print-production pipeline is one example, where page capture and analysis is used to monitor various aspects of printer behavior that affect quality. An inspection system designed to verify the functionality of printed security deterrents on product labels is another. If inspected items are moving, captured images can become blurred. To increase the throughput of such a system, even in some cases when strobing is used, it is necessary (1) to physically move the items at a higher speed, and (2) to maintain captured image quality *and* utility.

Motion blur can in part be addressed by a number of hardware or software restoration techniques. Methods have been analyzed or presented oriented towards different applications such as interpretation of long distance surveillance data [1], reduction of atmospheric effects [2], bi-level signals [3,4] and photography [5]. More general techniques have been developed as well, varying in complexity [6–8]. Nevertheless, most of these restoration techniques have been performed without any sense of how image *utility* is affected by the restoration process. In addition, de-blurring algorithms often assume prior knowledge the blur operator. Blur estimation techniques have been proposed based on numerous ideas, including transparency [9], analysis of ringing artifacts [7], iterative quadratic programming [4] and natural image models [10].

Several difficulties can arise when attempting to *compare* restoration techniques. One widely used comparison tactic is to apply quality assessment algorithms that quantify differences between restored and original images, and to determine which candidate technique generates the best result. With many types of image data, however, there is no way of obtaining a true original signal. Furthermore, in order to optimize a comparative quality assessment algorithm, a practitioner must understand how the values returned by the assessment algorithm affect a given application. Finally, some popular quality assessment algorithms are computationally intensive.

Barcode *readability*, i.e., the degree to which a barcode can be successfully interpreted, is presented as an objective, quantitative measurement by which different blur estimation techniques can be compared, in an attempt to solve some of these problems. Barcodes are advantageous for this purpose because (1) they are found on many types of printed documents (papers, tickets, labels, packages, etc.), (2) original barcode information requires little storage to represent and convey to inspection devices, and (3) barcode signals have structure that can be leveraged to create more efficient calibration tools. The problem of estimating a (1-D) blur operator from an image of a barcode is addressed with a solution that is applicable with other bi-level image data. It is shown that a blind barcode-based approach outperforms state-of-the-art alternatives in terms of speed and accuracy.

This paper is organized as follows. A quantitative framework for evaluating blur estimation performance is presented in Section 2, along with a degradation model. Section 3 proposes a barcode-based strategy to estimate a blur operator. Section 4 discusses performance testing, and concluding remarks are offered in Section 5.

2. MEASURING BARCODE READABILITY

In a document imaging framework, some of the problems associated with comparing general image restoration tech-

Fig. 1. An original, digital barcode (top), a *simulated* printed + imaged version generated using the linear model in (2) (left), and an actual printed + imaged version of the same barcode, captured in motion (right). Though noise has been ignored, the model reasonably represents the actual image.

niques are less of a concern. For example, since many applications involve a printing-imaging (PI) cycle, original (pre-acquisition) image data are often available for comparison purposes. On the other hand, some document inspection devices lack the resources necessary to perform traditional image-quality-metric-based analysis, which can occur if (1) the inspection device is too lightweight to perform the necessary computations, or (2) there is insufficient bandwidth required to capture an entire document moving at speed. In practice, these issues are addressed by focusing on subregions of images.

The use of structured printed markings, specifically barcodes (bi-level signals), is proposed to circumvent some of these problems. A barcode signal represents a certain type of document segment that does not require much storage to capture or analyze, and has other convenient properties. An example signal is illustrated in Figure 1. A PI cycle can be modeled as a linear lighting distortion coupled with a convolutional application of motion blur. If $b(x, y)$ denotes an original barcode, the model version detected after a PI cycle is given by

$$\begin{aligned} \hat{b}(x,y) &= \sum_{k=-H/2}^{H/2-1} h(k)(M \cdot b(x-k,y)+B) && (1) \\ &= M \cdot (h * b)(x,y) + B, && (2) \end{aligned}$$

where M and B are the lighting distortion parameters and $h(x, y)$ represents the blur operator as a filter with H non-zero taps. Estimation of the lighting distortion parameters can be performed in a number of different ways, but this topic is not the focus of this work. In reality, barcodes signals that have been printed and re-imaged in motion are modified by a plurality of degradations including optical blur, noise, and geometric distortions [11]. The criteria chosen to estimate the optimal blur operator, however, does not depend explicitly on these parameters so they are ignored.

The goal of a calibration algorithm designed to compensate for motion blur is to model the operator $h(x, y)$ as accurately as possible. The optimal blur operator is determined as that which yields the best barcode reading performance. Towards this goal, readability could be defined as the fraction of bars that decode correctly. This notion is intuitive, but is not necessarily convenient for optimization purposes since it requires a barcode reading procedure to be invoked. Instead, an image-based metric is used as a proxy for readability, and is defined as follows.

For simplicity, it is assumed that $h(x, y)$ represents motion in the x-direction, i.e., is essentially a one-dimensional blur operator h(x). Let $b_{blur}(x, y)$ denote the barcode $b(x, y)$ after being printed and captured in motion. Then, the optimal estimate for $h(x)$ is

$$\hat{h}^*(x) = \underset{\hat{h}(x)}{argmax}(\underset{b'(x,y)}{max}\ \rho_y(\hat{h}(x), b'(x,y), b_{blur}(x,y)), \quad (3)$$

where $\rho_x(\cdot,\cdot,\cdot)$ is given by

$$\begin{aligned} &\rho_x(\hat{h}(x), b'(x,y), b_{blur}(x,y)) = \quad (4) \\ &\underset{x}{corr}(M \cdot (\hat{h}(x) * \underset{y}{mean}\{b'(x,y)\}) + B, \underset{y}{mean}\{b_{blur}(x,y)\})). \end{aligned}$$

The function $\rho_x(\cdot)$ computes the correlation between (vertically-averaged one-dimensional) profiles of the detected barcode signal and the estimate signal $b'(x, y)$ modified by the degradation model. This readability criteria is proposed (1) because the original signal is bi-level and is further constrained to barcode symbologies, it can be computationally feasible to test all possible barcodes, (2) $\rho_x(\cdot)$ outputs a continuum of values, and (3) it implicitly describes a blur operator that is "good enough", i.e., any one that leads to correct barcode decoding via maximization of $\rho_x(\cdot)$ over $b'(x, y)$.

3. FAST BARCODE-BASED BLUR ESTIMATION

A simple, computationally efficient method can be used to approximate $h(x, y)$. For convenience, it is assumed that the blur operator represents an H-tap filter with values equal to $1/H$. The key is that the magnitude of the (horizontal) difference between adjacent samples of $b(x, y)$ to be either 0 or 1. Applying the distortion model, the magnitude of the difference between adjacent samples in $\hat{b}(x, y)$ must be either 0 or M/H. This property is easiest to visual in a blurred version of a binary signal with only one transition (see Figure 2).

A *similar* property holds for the *average* magnitude difference between values of $\hat{b}(x, y)$, which is useful because of the inevitable presence of noise. Since in reality only $b_{blur}(x, y)$ can be examined, the magnitude differences must be further analyzed in order to estimate the ratio $\frac{M}{H}$. Let $a(x, y)$ denote this difference, i.e., $a(x, y) = |b_{blur}(x, y) - b_{blur}(x + 1, y)|$. In the low noise case, when the values of $a(x, y)$ are large enough, the majority of the values of $a(x, y)$ are due to differences in adjacent samples of $b_{blur}(x, y)$ instead of noise. If the noise is zero mean, however, the average value of $a(x, y)$ (when $a(x, y)$ is large enough) will be close to $\frac{M}{H}$. H can thus be estimated using

$$\hat{H} = \underset{y}{median}\{M \cdot \big(\underset{k:a(k,y)>T_a}{mean}\{a(k,y)\}\big)^{-1}\}, \quad (5)$$

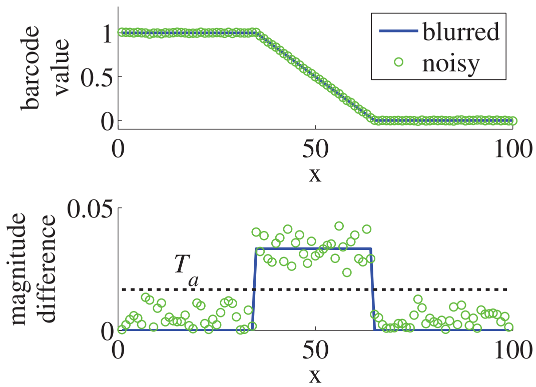


Fig. 2. Example horizontal profiles noise-free and noisy barcodes, blurred by a length-30 moving average filter, and the associated horizontal magnitude differences. In both cases, the average difference between adjacent pixels in the center of the plot is about $\frac{1}{30}$.

for some threshold T_a.

In a noise-free setting, choosing $T_a = mean_{x,y}\{a(x, y)\}$ will recover the blur operator exactly. Testing indicates that this choice can be reasonable in practice, at least in the context of blurred barcode (bi-level) signals, where the unblurred version has roughly the same amount of "black" and "white" values. To be applicable for more general types of signals, T_a must be chosen strategically to ignore the effects of noise, but not of blurring adjacent samples. Once $\hat{H}$ is known, the quantity $\hat{h}(x)$ can be computed via

$$\hat{h}(x) = \begin{cases} \frac{1}{\hat{H}} & -\frac{\hat{H}}{2} < x < \frac{\hat{H}}{2} \\ 0 & \text{else} \end{cases} . \tag{6}$$

4. RESULTS AND DISCUSSION

Preliminary testing was performed with a Logitech QuickCam 4000 and a HP C3180 AiO printer. Images were preprinted, then moved through the printer (as if form feeding a blank page). The degree of blur induced in the captured images was controlled via camera position and light source configuration. Testing occurred with an incandescent lamp placed near the printer. The speed of the moving pages was roughly 4.7 ft./s. = 280 ft/min.

4.1. Effects of Noise

Two types of methods are compared in terms of accuracy and robustness to noise: a traditional edge-based strategy (where blur is determined by the extent of the transition region between a large black rectangle and a white background), and the proposed approach. The blur estimation strategies were applied after lighting distortion parameters were estimated via auxiliary markings. Barcode signals were printed, imaged and segmented out of the captured image. Gaussian noise

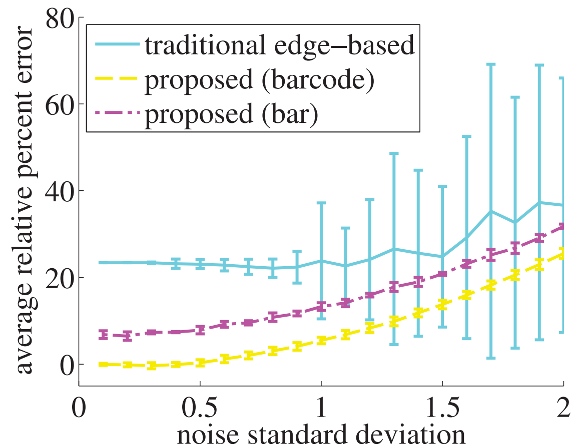


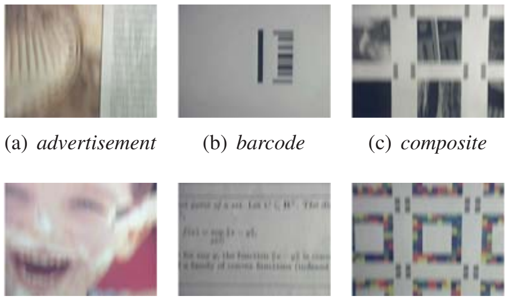
Fig. 3. Comparison between the proposed approach applied to a barcode signal, the proposed approach applied to a signal consisting of a single black bar surrounded by white, and a traditional edge-based estimator that examines the transition between the same black bar and the white background. The error bars denote standard deviation. For this test, the barcode-based approach yields the most consistent estimates.

was then added to the PI cycled results. The proposed approach was first used to estimate the blur diameter with the noisy barcode and these measurements were compared to an edge-based estimate of the blur diameter, computed by determining the width of the transition region between the blurred black bar and the white background. 200 different signals per noise standard deviation value were created, and twenty different standard deviations, evenly spaced between 0.1 and 2.0, were tested. The same procedure was also performed applying the proposed method on PI cycled images of solid black bars. Ground truth blur diameter was established via (4), constraining the search to include moving-average filters.

Results of this experiment are illustrated in Figure 3, which plots the relative percent error between the desired (optimal) blur diameter and the estimated blur diameter. For noise standard deviations below 1.0, all methods start to yield increasingly similar results. The proposed method is more robust to the addition of noise in general, and is definitely more consistent, as indicated by the error bars. In general, for this test set, blur diameter estimates that were within fifteen percent of the optimal estimate yielded perfect barcode decoding performance (and the proposed method achieved this result for at least half the tested amounts of noise).

4.2. Comparison with Other Approaches

The proposed approach is compared to several other state-of-the-art blind methods, specifically one designed for general images [7], and another more recent approach that leverages bi-level segments of general images [8]. Because each method is arguably strongest when applied to different types of image data, a set of images consisting of barcode, text, pho-



(a) *advertisement* (b) *barcode* (c) *composite*

(d) *photo* (e) *text* (f) *tile*

Fig. 4. Sample regions from images used to compare the proposed blur estimation methodology with those presented in [7, 8]. Each image was captured in motion from printed pages moving at approximately the same speed.

Table 1. Comparison of the blur operators estimated by the proposed method and those presented in [7] and [8].

image name	correlation (ρ_x)			allows correct decoding?		
	[7]	[8]	proposed	[7]	[8]	proposed
advertisement	**0.77**	0.67	-	no	no	no
barcode	0.78	**0.97**	0.94	no	**yes**	**yes**
composite	0.83	0.89	**0.94**	no	no	**yes**
photo	0.78	**0.80**	-	no	no	no
text	0.83	**0.98**	0.94	no	**yes**	**yes**
tile	0.81	0.81	**0.94**	no	no	**yes**

tograph, and composite images captured at speed via the same process were used (see Figure 4) for comparison purposes. All images in this test were captured from pages moving at the same speed. The goal was to determine whether or not the blur operator estimated from a sample image could be used to decode a barcode captured at the same speed. Note that the proposed method is not designed for general purpose image data. For this test, $T_a(y)$ was set to the standard deviation of noise in the captured image of a blank page. If for a given image there are no values of $a(x, y)$ greater than this threshold, it indicates that the image is unsuitable for use with the proposed estimation scheme, since ρ_x cannot be computed. Put another way, there is a built-in mechanism that can attempt to determine if a tested image is a bi-level image.

Results are illustrated in Table 1. The proposed method yields excellent performance when applied to blurred bi-level signals; it decodes all the bi-level and "near bi-level" signals (*barcode*, *composite*, *text*, *tile*) with perfect accuracy. The method in [8] uses detected bi-level segments in a more sophisticated manner, and as a result yields the best correlation performance for two of the bi-level signals. The technique in [7] yields the best performance on *advertisement*, which is difficult to analyze due to its smooth content.

Table 2 illustrates the result of a different test. Barcode images were printed from randomly generated symbols, and then captured at speed using the same technique as in the previous test. Fifty images were generated. In this evaluation, barcodes were printed, image and segmented out of the background prior to applying a blur estimation scheme. The proposed method correctly decoded 70 percent of the imaged barcodes, whereas the other tested method decoded none, which is a stark contrast to the comparative percent of correctly decoded individual bars. Due to its simplicity, the proposed method is several orders of magnitude faster than that given in [7].

Table 2. A comparison of barcode reading performance achieved by the proposed method and that presented in [7].

method	% individual bars correctly decoded	% barcodes correctly decoded	mean time (s)
proposed	**97.5**	**70**	**0.013**
[7]	82.0	0	58.337

5. CONCLUSION

This paper proposes a barcode-based functional strategy for evaluating blur restoration pipelines. A simple estimation strategy was also discussed that can be used to estimate blur diameter if a barcode signal is present, even if the barcode signal is not known. It is applicable on any inspection device for processing data that includes barcode symbols, and can be used in conjunction with other blurred bi-level signals. The proposed method was tested using images collected with true induced motion blur. It compares favorably to edge-based methods and state-of-the-art approaches to blind modeling

The authors thank Carl Staelin for his input on robustness to noise and Po-Hau Huang for kindly generating results.

6. REFERENCES

[1] J. Ma and F.-X. Le Dimet, "Deblurring from highly incomplete measurements for remote sensing," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 47, Mar. 2009.

[2] D. Li, R. Mersereau, and S. Simske, "Atmospheric turbulence degraded image restoration using principle component analysis," *IEEE Geosience and Remote Sensing Letters*, 2006.

[3] T.-H. Li and K.-S. Lii, "A joint estimation approach for two-tone image deblurring by blind deconvolution," *IEEE Trans. Im. Proc.*, vol. 11, pp. 847–858, Aug. 2002.

[4] E. Y. Lam, "Blind bi-level image restoration with iterated quadratic programming," *IEEE Trans. Circuits and Systems-II Express Briefs*, vol. 54, pp. 52–57, Jan. 2007.

[5] R. Banner and C. Staelin, "Removing motion blurs from a single photograph (HPL-2007-19)," Tech. Rep., Hewlett-Packard, Co., 2007.

[6] R. Neelamani, H. Choi, and R. Baraniuk, "ForWaRD: Fourier-wavelet regularized deconvolution for ill-conditioned system," *IEEE Trans. Sig. Proc.*, vol. 52, Feb. 2004.

[7] Q. Shan, J. Jia, and A. Agarwala, "High-quality motion deblurring from a single image," *ACM Transactions on Graphics (SIGGRAPH)*, 2008.

[8] P.-H. Huang, Y.-M. Lin, H.-L. Yang, and S.-H. Lai, "Image deblurring by exploiting inherent bi-level regions," in *Proc. ICIP*, 2009, pp. 1321–1324.

[9] J. Jia, "Single image motion deblurring using transparency," in *CVPR*, 2007.

[10] S. Hongwei, M. Desvignes, and Y. Yunhui, "Motion blur adaptive identification from natural image model," in *Proc. ICIP*, 2009, pp. 137–140.

[11] K. Solanki, U. Madhow, B. S. Manjunath, S. Chandrasekaran, and I. El-Khalil, "'Print and Scan' resilient data hiding in images," *IEEE Trans. Information Forensics and Security*, vol. 1, pp. 464–478, Dec. 2006.