Pattern Recognition Letters 34 (2013) 124–130

Contents lists available at SciVerse ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Two-dimensional bar code out-of-focus deblurring via the Increment Constrained Least Squares filter

Ningzhong Liu *, Xingming Zheng, Han Sun, Xiaoyang Tan

College of Computer Science & Technology, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

ARTICLE INFO

Article history:
Received 3 April 2012
Available online 21 September 2012
Communicated by G. Borgefors

Keywords:
Two-dimensional bar code
Image deblurring
Increment Constrained Least Squares filter

ABSTRACT

When a two-dimensional bar code is away from a camera's focus, the image is blurred by the convolution of the point spread function. In the presence of noise, the out-of-focus deblurring is an ill-posed problem. The two-dimensional bar code image has a very special form, making deblurring feasible. This paper proposes a fast deblurring algorithm called the Increment Constrained Least Squares filter that is specifically designed for two-dimensional bar code images. After analyzing the bar code image, the standard deviation of the Gaussian blur kernel is obtained. Then, the bar code image is restored through on iterative computations. In each iteration, the bi-level constraint of the bar code image is efficiently incorporated. Experimental results show that our algorithm can obtain better bar code image quality compared with existing methods. Our method can also improve the reading depth of field, which is an important performance parameter for bar code readers.

1. Introduction

The use of traditional one-dimensional bar codes has been greatly limited by their small information capacity. For this reason, the two-dimensional bar code was developed (Vangils, 1987). The two-dimensional bar code has high density, has an error correction ability, and can represent multiple forms of language, text, and image data with encryption (Liu and Doermann, 2008). At present, the most commonly used type of the two-dimensional bar code is the matrix bar code (Vangils, 1987; Renato et al., 2006), which consists of a matrix of elements. Each element represents the value of 1 or 0. Representative matrix bar code protocols include Data Matrix, QR Code and Maxi Code (Renato et al., 2006).

In this paper, the Data Matrix bar code, one of the most widely used two-dimensional bar code protocol (Renato et al., 2006), is used to study two-dimensional bar code deblurring technology. The method and idea presented here can also be applied to other two-dimensional bar code protocols, such as PDF417, QR Code and Maxi Code. Fig. 1(a) shows a Data Matrix bar code symbol. The symbol consists of data regions that contain nominally square modules set out in a regular array, as shown in Fig. 1(b). The symbol is surrounded by the finder pattern, which is indicated in Fig. 1(c). Two adjacent sides, the left and lower sides, form the "L" shaped boundary. The two opposite sides are made up of alternating dark and light modules. The detailed description of this protocol can be found in the Data Matrix ISO international standard (ISO, 2006).

For a long time, the problem of bar code decoding was closely related to edge detection (Joseph and Pavlidis, 1994; Youssef and Salem, 2007; Yang et al., 2012). However, if the bar code's surface is not at the camera' focal plane, the signal is blurred by the convolution of the point spread function (Joseph and Pavlidis, 1994; Selim, 2004). The longer the distance, the more blurred the observed signal. Currently, recognition methods based on edge detection are no longer sufficient. Although bar code readers are already well-established products, how to deblur the signal is still a hot point. Deblurring can improve the depth of field, which is an important performance parameter for bar code readers (Turin and Boie, 1998). Besides bar code readers, in recent years, mobile phones have been used to recognize bar codes and then interact with internet systems (Kato and Tan, 2007; Yang et al., 2012). However, captured images are blurred because of the lack of auto-focus on most phones (Eisaku et al., 2004; Thielemann et al., 2004). Thus captured images need deblurring before recognition.

Various algorithms have been developed to deblur bar code signals. Joseph and Pavlidis (1993, 1994) calculated the standard deviation of the point spread function and then compensated bar code edge locations. Turin and Boie (1998) applied the deterministic expectation–maximization (EM) algorithm to deblur bar code signals. Shellhammer et al. (1999) obtained bar code edges using selective sampling and edge-enhancement filter. Okol'nishnikova (2001) applied recursive step-by-step optimization formulas to recognize bar codes. Marom et al. (2001) and Kresic-Juric (2005) analyzed the statistical properties of the edge localization errors of bar code signals corrupted by speckle noise. Kresic-Juric et al. (2006) applied the Hidden Markov Model (HMM) to edge detection

* Corresponding author. Tel.: +86 2584896490.
E-mail address: lnz66@hotmail.com (N. Liu).

0167-8655/$ - see front matter
http://dx.doi.org/10.1016/j.patrec.2012.09.006

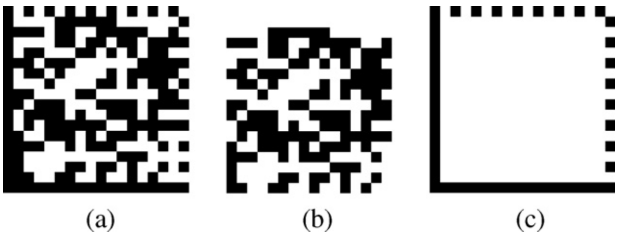

Fig. 1. Data Matrix code structure: (a) Data Matrix bar code, (b) data region, (c) finder pattern.

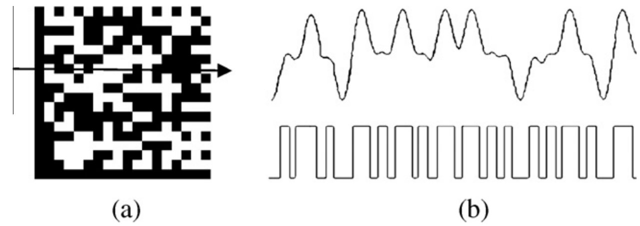

Fig. 2. The signal after the convolution: (a) the signal of a line in the bar code image, (b) the degraded bar code signal of a line.

in bar code signals. Kim and Lee (2007) applied the penalized nonlinear squares objective function to deblur bar code signals. Liu and Sun (2010) applied iterative Fourier transform to process degraded signals.

However, these methods are largely designed for one-dimensional bar codes. They cannot deblur the two-dimensional bar code image effectively. In addition, these methods are based on signal enhancement. They are effective when the standard deviation of the blur convolution kernel is comparable to the smallest module width of the bar code (ISO, 2006; Liu and Doermann, 2008). However, when the reader is held to far from the bar code, the standard deviation of the blur kernel becomes large due to the optics characteristics of imaging system (Selim, 2004). Thus these approaches would be at a significant disadvantage.

In this paper, we use image restoration technology to design a deblurring algorithm specifically for the two-dimensional bar code. Image deblurring aims to recover the original image from an observed signal. The model of the problem can be expressed as (Gonzalez and Woods, 2002)

$$g = h * f + n, \tag{1}$$

where g is the observed image, h is the point spread function, f is the original image, and n is the additive noise. In optical systems of bar code reader, h is a Gaussian function (Joseph and Pavlidis, 1994; Kim and Lee, 2007):

$$h(x, y) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right). \tag{2}$$

Many methods have been proposed to restore blurred images, such as the classical Inverse filter and the Wiener filter. Recently, methods based on regularization techniques (Bar et al., 2006; Mignotte, 2006; Beck and Teboulle, 2009; Liao and Ng, 2011; Cai et al., 2012) and sparse representation (Mairal et al., 2008; Elad et al., 2010; Dong et al., 2011) have been extensively studied. However, these methods require large computations, making them inefficient for use in bar code readers and mobile phones. Here, we design a fast deblurring method called the Increment Constrained Least Squares filter to restore the bar code image. The number of iterations is not large. In each iteration, the bi-level constraint of the bar code image is efficiently incorporated.

The paper is organized as follows. The standard deviation estimation method is given in Section 2. Section 3 describes the deblurring method. Experimental results are discussed in Section 4, and conclusion is given in Section 5.

2. Blur kernel estimation

In general, the Gaussian blur kernel is the most common degradation function of bar code readers' optical systems (Joseph and Pavlidis, 1994; Kim and Lee, 2007). Before deblurring the image, we need to estimate the standard deviation of the blur kernel. There are only two gray values in the bar code. After the acquisition of the image, we designate the gray value of the white modules as v_1 and the gray value of the black modules as v_2. As Fig. 2(a) shows, considering the signal obtained by scanning the bar code image with a horizontal line, in the ideal situation, the edge information will be a series of steps, as shown in the bottom of Fig. 2(b). In the actual blurred image, however, because of the convolution with the blur kernel function, a gradual change is shown at each edge, as shown in the top of Fig. 2(b).

We can denote the x-coordinate of the "L" shaped finder pattern's (ISO, 2006) left edge as x_0. We can know the gray values of the pixels on the left of x_0 are v_1, and that on the right of x_0 are v_2. The signal near the "L" shaped finder pattern's left edge is determined only by the x-coordinate (ISO, 2006). Thus, the signal near the edge can be expressed as one-dimensional form:

$$b(x) = (v_2 - v_1)U(x - x_0) + v_1, \tag{3}$$

where $U(x)$ is the unit step function (Joseph and Pavlidis, 1994).

Eq. (2) shows the Gaussian blur function is separable:

$$h(x, y) = \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(\frac{-x^2}{2\sigma^2}\right) \cdot \exp\left(\frac{-y^2}{2\sigma^2}\right). \tag{4}$$

The "L" shaped finder pattern' length (ISO, 2006) is much larger than the standard deviation of the Gaussian blur function. Therefore, the signal near the "L" shaped finder pattern can be simplified to a one-dimensional Gaussian degradation model (Joseph and Pavlidis, 1994):

$$w(x) = b(x) * h_0(x). \tag{5}$$

After normalization, h_0 can be expressed as the one-dimensional Gaussian blur function:

$$h_0(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-x^2}{2\sigma^2}\right). \tag{6}$$

From the differential property of the convolution operation (Shellhammer et al., 1999), the first-order derivative of the signal $w(x)$ is

$$\begin{aligned} w'(x) &= [b(x) * h_0(x)]' = h_0(x) * b'(x) \\ &= h_0(x) * [(v_2 - v_1)U(x - x_0)] + v_1]' \\ &= (v_2 - v_1) \cdot h_0(x) * U'(x - x_0). \end{aligned} \tag{7}$$

From the definition of $U(x)$, it is known that

$$U'(x - x_0) = \delta(x - x_0). \tag{8}$$

Here, $\delta(x)$ is the Dirac Impulse Function. The property of the Dirac Impulse Function implies that

$$h_0(x - x_0) * U'(x) = h_0(x) * \delta(x - x_0) = h_0(x - x_0). \tag{9}$$

From Eqs. (7) and (9), the first-order derivative of the signal $w(x)$ can be written as

$$w'(x) = (v_2 - v_1) \cdot h_0(x - x_0) = \frac{(v_2 - v_1)}{\sqrt{2\pi}\sigma} \exp\left[\frac{-(x - x_0)^2}{2\sigma^2}\right]. \tag{10}$$

The second order derivative of $w(x)$ can be obtained by continuing the above process, yielding

$$w''(x) = -\frac{(v_2 - v_1)\cdot(x - x_0)}{\sqrt{2\pi}\sigma^3}\exp\left[-\frac{(x-x_0)^2}{2\sigma^2}\right]. \tag{11}$$

Eq. (11) shows that $w''(x)$ is zero when $x = x_0$. Therefore, we can use the second derivative to find x_0. In addition, from Eq. (10), when $x = x_0$, $w'(x_0) = \frac{(v_2-v_1)}{\sqrt{2\pi}\sigma}$. Therefore, the standard deviation σ of the Gaussian function can be calculated according to the following equation:

$$\sigma = \frac{(v_2 - v_1)}{\sqrt{2\pi}\cdot w'(x_0)}. \tag{12}$$

3. Deblurring the image

Solving Eq. (1) under the influence of noise is an ill-posed problem (Gonzalez and Woods, 2002). Regularization-based techniques have been extensively studied to solve this problem (Bar et al., 2006; Mignotte, 2006; Beck and Teboulle, 2009; Liao and Ng, 2011; Cai et al., 2012), but these methods require large computations, making them inefficient for use in bar code readers and mobile phones. Furthermore, these methods are not designed for two-dimensional bar codes and cannot solve this kind of blurring problem effectively.

A bar code is composed of black and white modules, so the bar code image is binary, i.e., 0 or 1. Under this constraint, iterative methods are suitable for deblurring the bi-level image. In each iteration, the spatial domain constraint can be efficiently incorporated. The Increment Wiener filter (Zou and Rolf, 1995; Li et al., 2011) with iterative form has been reported to have a better restoration performance than the Wiener filter. The Increment Wiener filter is used in conjunction with object domain constraint and can improve the image quality after restoration. However, the Increment Wiener filter needs to know the power spectra of the noise. It is difficult to suppress noise effectively. Here, we design a fast iterative deblurring algorithm based on the Constrained Least Squares filter (Hunt, 1973).

We can express Eq. (1) in vector–matrix form (Gonzalez and Woods, 2002):

$$\mathbf{g} = \mathbf{Hf} + \mathbf{n} \tag{13}$$

In the Constrained Least Squares filter, a matrix $\mathbf{Q}$ is selected to enforce some degree of smoothness on the restored image. In general, let $\mathbf{Q}$ corresponded to a high pass convolution filtering operation, such as the Laplacian. Let $\hat{\mathbf{f}}$ be an estimation of the solution to Eq. (13). Thus, what is desired is to find the minimum of a criterion function $\|\mathbf{Q}\hat{\mathbf{f}}\|^2$ subject to the constraint $\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2 = \|\mathbf{n}\|^2$. The problem can be set up as the minimization of the object function (Gonzalez and Woods, 2002):

$$W(\hat{\mathbf{f}}) = \|\mathbf{Q}\hat{\mathbf{f}}\|^2 + \lambda\left(\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2 - \|\mathbf{n}\|^2\right), \tag{14}$$

where λ is a Lagrange multiplier. We set the derivative of $W(\hat{\mathbf{f}})$ with respect to $\hat{\mathbf{f}}$ to zero:

$$\frac{\partial W(\hat{\mathbf{f}})}{\partial \hat{\mathbf{f}}} = 2\mathbf{Q}'\mathbf{Q}\hat{\mathbf{f}} - 2\lambda\mathbf{H}'(\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}) = 0. \tag{15}$$

Solving for $\hat{\mathbf{f}}$ yields

$$\hat{\mathbf{F}} = \left(\mathbf{H}'\mathbf{H} + \frac{1}{\lambda}\mathbf{Q}'\mathbf{Q}\right)^{-1}\mathbf{H}'\mathbf{g}. \tag{16}$$

The frequency domain specification is

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}\right]G(u,v), \tag{17}$$

where $\gamma = 1/\gamma$.

Now, we modify the Constrained Least Squares filter with an iterative form. In each iteration, the spatial domain constraint can be efficiently incorporated to improve the image quality. In this paper, we call it the Increment Constrained Least Squares filter (ICLS). In the Increment Constrained Least Squares filter, we use an error array as

$$S(u,v) = G(u,v) - \hat{F}(u,v)H(u,v), \tag{18}$$

where $G(u,v)$ is the frequency of the observed image, $\hat{F}(u,v)$ is the frequency of the restored image, and $H(u,v)$ is the frequency of the blur kernel function. For an initial estimation $\hat{F}_{\text{old}}(u,v)$, the initial error array is

$$S_{\text{old}}(u,v) = G(u,v) - \hat{F}_{\text{old}}(u,v)H(u,v). \tag{19}$$

We hope to find a new estimation $\hat{F}_{\text{new}}(u,v)$ to reduce $\|S(u,v)\|^2$. Combining Eqs. (17) and (19), we get

$$\hat{F}_{\text{new}}(u,v) = \frac{|H(u,v)|^2\hat{F}_{\text{old}}(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2} + \frac{H^*(u,v)S_{\text{old}}(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}. \tag{20}$$

Its approximated as

$$\hat{F}_{\text{new}}(u,v) = \hat{F}_{\text{old}}(u,v) + \frac{H^*(u,v)S_{\text{old}}(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}, \tag{21}$$

giving the new error array

$$\begin{aligned} S_{\text{new}}(u,v) &= G(u,v) - \hat{F}_{\text{new}}(u,v)H(u,v) \\ &= G(u,v) - \left[\hat{F}_{\text{old}}(u,v) + \frac{H^*(u,v)S_{\text{old}}(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}\right]H(u,v) \\ &= S_{\text{old}}(u,v) - \left[\frac{H^*(u,v)S_{\text{old}}(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}\right]H(u,v) \\ &= \frac{\gamma|Q(u,v)|^2}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}S_{\text{old}}(u,v). \end{aligned} \tag{22}$$

Because $|H(u,v)|^2 \geqslant 0$ and $\gamma|Q(u,v)|^2 \geqslant 0$, we immediately have

$$\|S_{\text{new}}(u,v)\|^2 < \|S_{\text{old}}(u,v)\|^2. \tag{23}$$

Thus, each iteration of the ICLS filter can reduce the error array.

The value of γ has a subtle effect on the iteration process. If the value of γ is large, the solution will become smooth and the noise tolerance will be improved. However, a value of γ that is too large can increase the number of iterations. On the other hand, a value of γ that is too small will lead to an unstable process, and the appearance of the estimation will be unsmooth. In our experience, we can set

$$\gamma = (0.1 - 0.3)\frac{\max(|H(u,v)|)}{\max(|Q(u,v)|)}. \tag{24}$$

The ICLS method has been designed with an iterative form. After the inverse Fourier transform, the spatial domain constraints can be efficiently incorporated. The bar code consists of black and white square modules, so its histogram is bi-modal. Pixels of black modules form one peak. The gray value is B_1 to B_2. Pixels of white modules form the second peak and the gray value is W_1 to W_2. For a bi-modal histogram, it is easy to obtain the optimal threshold T. We can use the following constraint in the spatial domain to suppress oscillations in the image after each iteration

$$f_c(x,y) = \begin{cases} B_1 & f(x,y) < B_1, \\ B_2 & B_2 < f(x,y) < T, \\ W_1 & T < f(x,y) < W_1, \\ W_2 & f(x,y) > W_2. \end{cases} \tag{25}$$

We define the movement of the error array in Eq. (18) as

$$E_i(u,v) = \frac{\|S_i(u,v)\|^2 - \|S_{i+1}(u,v)\|^2}{\|S_i(u,v)\|^2}, \tag{26}$$

where $S_i(u,v)$ and $S_{i+1}(u,v)$ are the error arrays after ith and $(i+1)$th iterations of the ICLS filter. After each iteration, we compute $E_i(u,v)$. If $E_i(u,v) < \varepsilon$, we stop iterating. In general, ε can be set to 0.05. The complete framework of our algorithm is summarized below:

Algorithm Deblurring algorithm for two-dimensional bar code images

(1) Obtain an initial estimation:
$F_0(u,v) = \left[\frac{H^*(u,v)}{|H(u,v)|^2+\gamma|Q(u,v)|^2}\right]G(u,v).$
(2) Compute the new estimation:

$$S_k(u,v) = G(u,v) - F_k(u,v)H(u,v);$$

$$F_{k+1}(u,v) = F_k(u,v) + \frac{H^*(u,v)S_k(u,v)}{|H(u,v)|^2 + \gamma|Q(u,v)|^2}.$$

(3) Compute the movement of the error array $E_k(u,v)$. If $E_k(u,v) < \varepsilon$, stop iterating
(4) Add bi-level constraint in spatial domain:

$$f_{k+1}(x,y) = \mathrm{IFFT}(F_{k+1}(u,v));$$

Update $f_{k+1}(x,y)$ with Eq. (25); Go to step 2

4. Experimental results and comparisons

In this section, the deblurring performance of our algorithm is verified both on simulated blurred images and real blurred images. To simulate blurred images, the original images are blurred by a blur kernel and then additive Gaussian noise is added. For the real blurred images, we use a commercial handheld mobile bar code reader to collect data.

4.1. The number of iteration and computation time

Fig. 3(a) is the original clean Data Matrix bar code image. The image was blurred by the Gaussian blur kernel with $\sigma_b = W$, where W is the module's width (ISO, 2006). Then additive Gaussian noise with standard deviation $\sigma_n = 4$ was added. Fig. 3(b) is the noisy and blurred image. Then, the algorithm of this paper was carried out to deblur the bar code image. The resulting images after the 1st, 3rd, 5th and 7th iteration are show in Fig. 3(c)–(f). From Fig. 3, we observe that after 7 iterations our method improve the image quality efficiently.

A large value of the movement of the error array $E_i(u,v)$ defined in Eq. (26) indicates a large difference between two iterations. We summarize the values of $E_i(u,v)$ after each iteration. We see that when the number of iterations is more than 7 the values of $E_i(u,v)$ are stable and smaller than 0.05. This result indicates that 7–8 iterations are sufficient to recover the blurred image using our method. More iterations do not significantly improve the image quality.

Currently, most of bar code readers use ARM CPUs. Here, we compare the calculation time of the ICLS filter programmed on an ARM CPU with Matlab on a PC. Test images with resolutions of 320×240 and 640×480 were used. The computer's CPU is an Intel P9600 2.53 GHz. The ARM CPU is a Samsung 6410 running WinCE6.0 as operation system. For a 320×240 image, the calculation times of Matlab and the ARM are 1350 ms and 230 ms, respectively. For an image resolution of 640×480, the calculation times of Matlab and the ARM are 3250 ms and 670 ms, respectively. These experimental data show that the ARM is much faster at these calculations than the Matlab program. The calculation time of the ARM is no more than one second. Thus our algorithm can be realized on ARM CPUs in real-time.

4.2. Comparison of deblurring results using different methods

In this subsection, we compare our deblurring approach to existing deblurring methods, including the Increment Wiener filter (Zou and Rolf, 1995; Li et al., 2011), the Centralized Sparse Representation method (Dong et al., 2011), and the Alternating Minimization algorithm (Zhang, 2012) to show its effectiveness. The

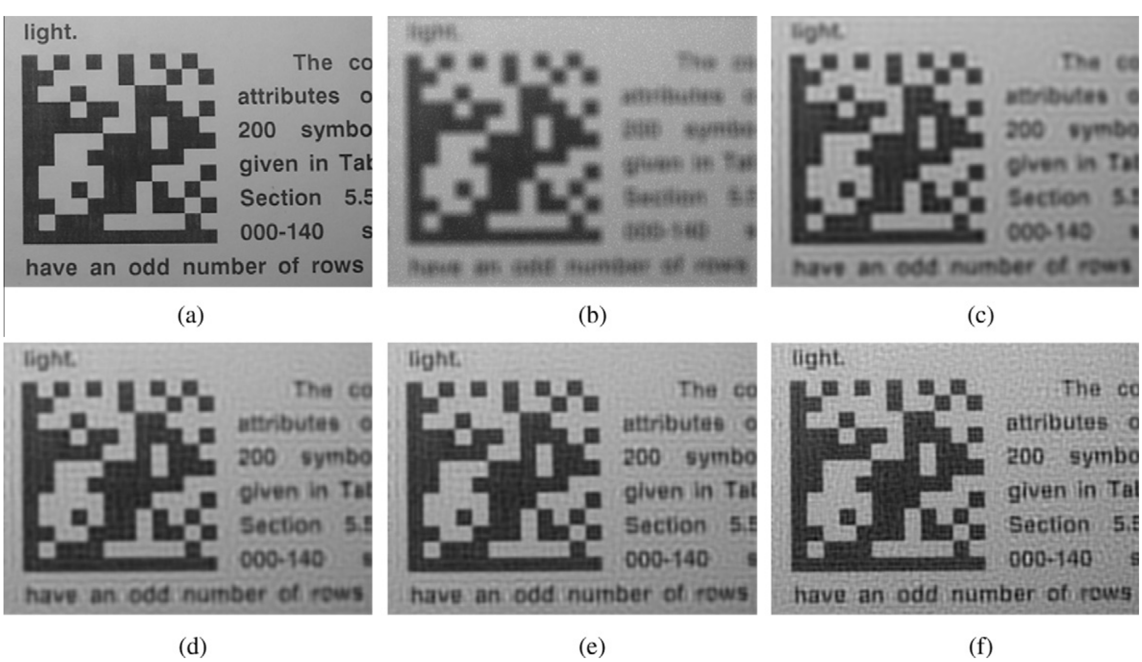

Fig. 3. Deblurring results: (a) original image, (b) noisy and blurred image, (c) the result after 1 iteration, (d) the result after 3 iterations, (e) the result after 5 iterations, (f) the result after 7 iterations.

Table 1
The PSNR for various Gaussian noise factors.

σ_n	PSNR				
	Before deblurring	IW	CRS	AM	ICSL
4	30.51	31.46	31.64	31.72	31.67
6	29.93	30.55	31.20	31.28	31.22
8	29.35	28.63	29.93	30.36	30.64
10	28.74	28.21	28.79	29.27	29.95
12	28.17	27.95	28.27	28.32	29.45

Centralized Sparse Representation method is a recently proposed approach that produces state-of-the-art results for nature images. The Alternating Minimization algorithm is also a recently proposed approach designed specifically for binary image, such as bar code and hand-written signatures. In this experiment, we denote the Increment Wiener filter, the Centralized Sparse Representation method, and the Alternating Minimization algorithm as IW, CSR, and AM, respectively. As before, we simulated a blur image by blurring the original image with the Gaussian blur kernel having a standard deviation σ_b equal to W, the module's width (ISO, 2006). Then, the additive Gaussian noise with standard deviation $\sigma_n = 4 - 12$ was added. Hundred Data Matrix bar code images were used as experimental dataset. After deblurring, the average PSNR results of these 100 images are reported in Table 1.

From Table 1, we can see that the proposed ICSL deblurring method significantly outperforms the IW method. The performance of the IW method decreases dramatically when the noise level σ_n increases, whereas our ICSL algorithm still has good performance when σ_n increases. Compared with the CRS method, our algorithm has similar performance when the noise level σ_n is not high. With an increase in σ_n, our algorithm yields better results. The CRS method is designed for nature images, and produces state-of-the-art results. Our algorithm is designed specifically for the two-dimensional bar code. In each iteration, the bi-level constraint of the bar code image is efficiently incorporate. Thus, our algorithm can obtain better result on two-dimensional bar codes. Compared with our algorithm, the AM algorithm has slightly better performance when the noise level σ_n is not high. However, with an increase in σ_n, our algorithm exhibits better robustness performance to recover bar code images from degraded signals under high noise influence.

On the other hand, in this experiment, the CRS algorithm converges in 80 iterations, and the calculation time of Matlab is about 500 s with Intel P9600 2.53 GHz. Our algorithm converges in 8 iterations and the calculation time of Matlab is within 1.5 s. The speed of the CRS method is much slower than our algorithm, so the CRS method is inefficient for use in bar code readers and mobile phones. In addition, at each iteration of AM algorithm, besides one FFT and one inverse FFT, the Newton method is used for obtaining the minimum value of a polynomial of the fourth order (Zhang, 2012). In this experiment, the calculation time of the AM algorithm is 2.2 s. This indicates that our algorithm is faster than the AM algorithm.

Visual comparisons of the deblurring methods are shown in Fig. 4. We observe that with an increase of the noise level σ_n, our method contains a lower level of noise in the restored image than both IW and AM methods. On the other hand, the result of the CSR method exhibits many oscillations in the image. In comparison with these three approaches, our ICSL method leads to the best performance under the influence of noise.

4.3. Scanning distance and deblurring range

The depth of field is an important performance parameter for bar code readers (Turin and Boie, 1998). The longer the distance, the more blurred the observed image will be. In this subsection, we test the scanning distance of our algorithm. We printed 200 Data Matrix bar codes with various module widths (ISO, 2006) as experimental data. Images were recognized using a GW-100

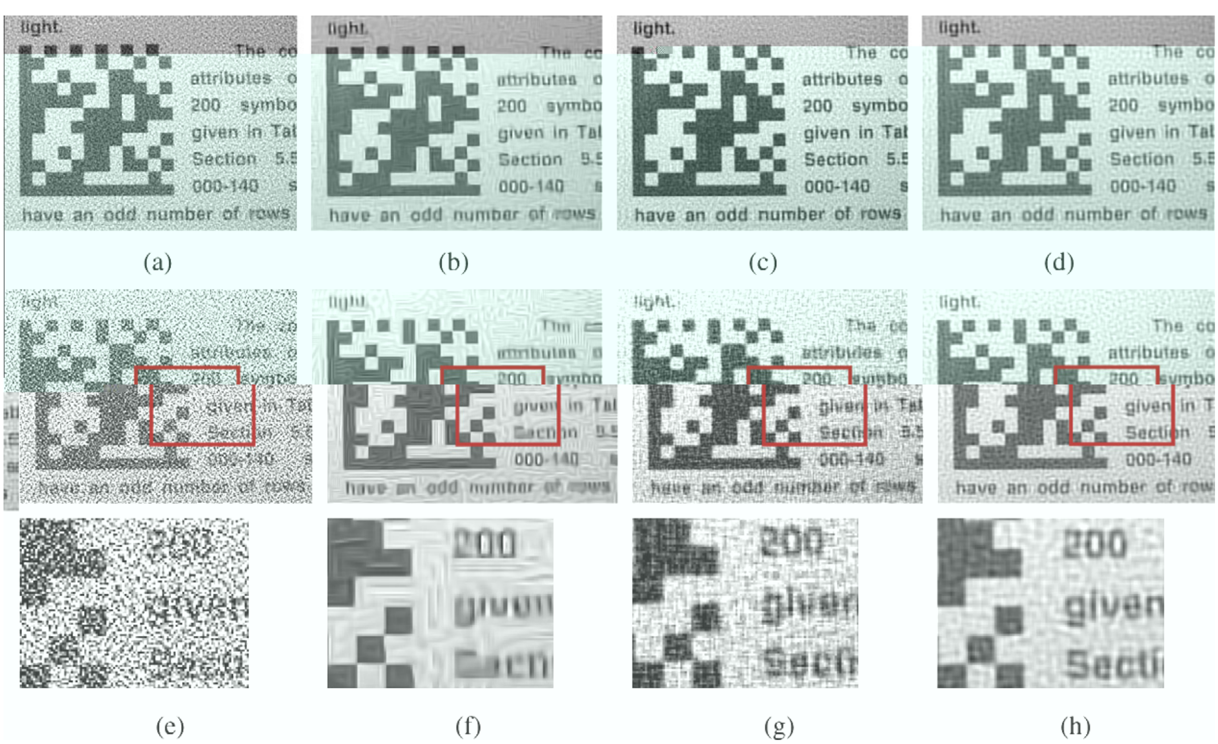

Fig. 4. Deblurring results comparisons: (a) the result of the IW with $\sigma_n = 4$, (b) the result of the CSR with $\sigma_n = 4$, (c) the result of the AM with $\sigma_n = 4$, (d) the result of the ICSL with $\sigma_n = 4$, (e) the result of the IW with $\sigma_n = 12$, (f) the result of the CSR with $\sigma_n = 12$, (g) the result of the AM with $\sigma_n = 12$, (h) the result of the ICSL with $\sigma_n = 12$.

Table 2
Comparison of scanning distance.

Bar code density (mils)	Scanning distance (cm)		Increase in scanning distance (%)
	GW-100	GW-100 with ICSL	
5	8.5	12.5	47.1
10	14.5	22.0	51.7
15	18.5	27.5	48.6
20	21.0	30.5	45.2

Table 3
The recognition rate for various blurring factors.

$\sigma_{b/W}$	Recognition rate				
	Before deblurring (%)	IW (%)	CSR (%)	AM (%)	ICSL (%)
0.75	96.5	99.5	100	100	100
1.0	76.5	91.25	95.5	97.0	97.5
1.25	55.5	83.5	92.25	94.75	94.5
1.5	15.5	67.0	82.0	87.25	88.5
1.75	0	57.75	70.75	74.5	76.75

commercial mobile handheld terminal of Partitek Inc. The CPU of the terminal is Samsung 6410 operating at a clock frequency of 800 MHz. The camera is an OV9650. We implemented our deblurring method in the GW-100 reader, and measured the new scanning distance. Bar code densities were measured in mils. An x mil bar code is one where the module has a width size of x/1000th of an inch. Table 2 summarizes the results of this study. This experiment shows that our method has at least a 45.2% increase in the maximum scanning distance and it can decode bar codes with higher densities.

The standard deviation σ_b of the Gaussian blur kernel is an important factor in the algorithm. If its value is large, the image will be severely blurred. Here, we test the recognition rates for various values of σ_b. First, 400 Data Matrix bar codes were generated randomly and the Gaussian blur kernel is applied. Then, we printed them and captured the images with the scanner. We deblurred the captured images using the algorithm proposed in this paper and then recognized them with bar code decoder ClearImage (ClearImage, 2010). This experiment was repeated for several values of σ_b. The recognition rate before deblurring and after deblurring is given in Table 3. The recognition rate is defined as the number of correctly recognized barcodes versus the total number of barcodes.

From the data in Table 3, we can see that the algorithm in this paper has good performance when σ_b increases. When σ_b/W is 1.75, we still get a recognition rate of 76.75%. Because the algorithm in this paper is based on image restoration rather than signal enhancement, it can process signals that are more blurred. Compared with the IW and the CSR algorithm, our method can get higher recognition rate. Compared with the AM algorithm, our method has similar recognition rate. However, our method is faster than the AM algorithm and has better result under the influence of high noise, as reported in Section 4.2.

5. Conclusion

When a bar code is away from a camera's focus, the image is blurred. Thus, it is necessary to process the signal before decoding the bar code. Two-dimensional bar code image has two gray: black and white. With this constraint, we use iterative computations to deblur bar code signals. In this paper, we designed a fast deblurring method called the Incremental Constrained Least Squares filter (ICSL) to restore bar code images. The method has an iterative form, so the spatial domain constraint can be efficiently incorporated after each iteration. The experiments show that the ICSL method based on iterative computations has good performance. It can recover bar code images from degraded signals under high noise influence and successfully improve the reader's depth of field.

Acknowledgment

The authors would like to thank referees for their comments to clarify the ideas of the paper. The authors are also grateful to ParTiTek Inc. and Newland Auto-ID Inc. for providing the hardware and data in the analysis. This research is supported in part by the National Natural Science Foundation of China (Nos. 60903104 and 61073112).

References

Bar, L., Sochen, N., Kiryati, N., 2006. Semi-blind image restoration via Munford–Shah regularization. IEEE Trans. Image Process. 15 (2), 483–493.

Beck, A., Teboulle, M., 2009. Fast gradient-based algorithms for constrained total variation image denoising and deblurring problems. IEEE Trans. Image Process. 18 (11), 2419–2434.

Cai, J., Ji, H., Liu, C., Shen, Z., 2012. Framelet-based blind motion deblurring from a single image. IEEE Trans. Image Process. 21 (2), 562–572.

ClearImage, 2010. <http://www.inliteresearch.com/homepage/products/tools.html>.

Dong, W., Zhang, L., Shi, G., 2011. Centralized sparse representation for image restoration. In: Proc. IEEE Internat. Conf. on Computer Vision, Barcelona, Spain.

Eisaku, O., Hiroshi, H., Lim, A.H., 2004. Barcode readers using the camera device in mobile phones. In: Proc. 2004 Internat. Conf. on Cyber worlds, Tokyo, Japan, pp. 260–265.

Elad, M., Figueiredo, M.A.T., Ma, Y., 2010. On the role of sparse and redundant representations in image processing. Proc. IEEE 98 (6), 972–982.

Gonzalez, R.C., Woods, R.E., 2002. Digital Image Processing. Prentice-Hall, Englewood Cliffs.

Hunt, B.R., 1973. The application of constrained least squares estimation to image restoration by digital computer. IEEE Trans. Comput. 22 (9), 805–812.

ISO/IEC 16022, 2006. Information technology – Automatic identification and data capture techniques – Data Matrix bar code symbology specification.

Joseph, E., Pavlidis, T., 1993. Deblurring of bilevel waveforms. IEEE Trans. Image Process. 2 (2), 223–235.

Joseph, E., Pavlidis, T., 1994. Bar code waveform recognition using peak locations. IEEE Trans. Pattern Anal. Machine Intell. 16 (6), 630–640.

Kato, H., Tan, K.T., 2007. Pervasive 2D barcodes for camera phone applications. IEEE Pervasive Comput. 6 (4), 76–85.

Kim, J., Lee, H., 2007. Joint nonuniform illumination estimation and deblurring for bar code signals. Opt. Express 15 (22), 14817–14837.

Kresic-Juric, S., 2005. Edge detection in bar code signals corrupted by integrated time-varying speckle. Pattern Recognition 38 (12), 2483–2493.

Kresic-Juric, S., Madej, D., Santosa, F., 2006. Applications of hidden Markov models in bar code decoding. Pattern Recognition Lett. 27 (14), 1665–1672.

Li, H., Lu, J., Shi, G., Zhang, Y., 2011. Real-time blind deconvolution of retinal images in adaptive optics scanning laser ophthalmoscope. Opt. Comm. 284 (13), 3258–3263.

Liao, H., Ng, M.K., 2011. Blind deconvolution using generalized cross-validation approach to regularization parameter estimation. IEEE Trans. Image Process. 20 (3), 670–680.

Liu, N.Z., Sun, H., 2010. Recognition of the stacked two-dimensional bar code based on iterative deconvolution. Imaging Sci. J. 58 (2), 81–88.

Liu, X., Doermann, D., 2008. VCode-pervasive data transfer using video barcode. IEEE Trans. Multimedia 10 (3), 361–371.

Mairal, J., Elad, M., Sapiro, G., 2008. Sparse representation for color image restoration. IEEE Trans. Image Process. 17 (1), 53–69.

Marom, E., Bergstein, L., Kresic-Juric, S., 2001. Analysis of speckle noise in bar-code scanning systems. Opt. Image Sci. 18 (4), 888–901.

Mignotte, M., 2006. A segmentation-based regularization term for image deconvolution. IEEE Trans. Image Process. 15 (7), 1973–1984.

Okol'nishnikova, L.V., 2001. Polynomial algorithm for recognition of bar codes. Pattern Recognition Image Anal. 11 (2), 361–364.

Renato, V., Sviatoslav, V., Oleksiy, K., 2006. Multilevel 2-D bar codes: toward high-capacity storage modules for multimedia security and management. IEEE Trans. Inf. Forensic Secur. 1 (4), 405–420.

Selim, E., 2004. Blind deconvolution of bar code signals. Inverse Prob. 20 (1), 121–135.

Shellhammer, S.J., David, G.P., Pavlidis, T., 1999. Novel signal-processing technology's in barcode scanning. IEEE Rob. Autom. Mag. 6 (1), 57–65.

Thielemann, J.T., Schumann-Olsen, H., Schulerud, H., Kirkhus, T., 2004. Handheld PC with camera used for reading information dense barcodes. In: Proc. IEEE Int. Conf. on Computer Vision and Pattern Recognition, Demonstration Program, Washington, DC.

Turin, W., Boie, R.A., 1998. Bar code recovery via the EM algorithm. IEEE Trans. Signal Process. 46 (2), 354–363.
Vangils, W., 1987. Two-dimensional dot code for product identification. IEEE Trans. Inf. Theory 33 (5), 620–631.
Yang, H., Alex, C., Jiang, X., 2012. Barization of low-quality barcode images captured by mobile phones using local window of adaptive location and size. IEEE Trans. Image Process. 21 (1), 418–425.
Youssef, S.M., Salem, R.M., 2007. Automated barcode recognition for smart identification and inspection automation. Expert Syst. Appl. 33 (4), 968–977.
Zhang, J., 2012. An alternating minimization algorithm for binary image restoration. IEEE Trans. Image Process. 21 (2), 883–888.
Zou, M.Y., Rolf, U., 1995. New algorithms of two-dimensional blind deconvolution. Opt. Eng. 34 (10), 2945–2956.