Recognition of the stacked two-dimensional bar code based on iterative deconvolution

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Abstract: Traditionally, the method of bar code recognition is based on edge detection. Because of the high density of the stacked two-dimensional bar code, the signal is severely blurred by the point spread function of the optical system. And this method is not suitable. In order to deblur the image, a deconvolution technique is necessary. Under the influence of noise, deconvolution is a type of ill-posed problem. Based on the idea of bar codes as bilevel waveforms, a novel bar code recognition algorithm rooted in iterative deconvolution is proposed in this paper. First, the bar code is rotated to be horizontal using the interpolation of sixteen points. After analysing the waveform, the system identification is accomplished. At last, the bar code waveform is reconstructed based on iterative computations. The results show that the performance of the algorithm proposed here is excellent. It can achieve higher recognition rates than previous models.

Keywords: bar code recognition, deconvolution, point spread function, bilevel waveform

1 INTRODUCTION

Bar code technology is an important way of automatic data identification.[1,2] Its recognition technology is a problem of edge detection.[3] For a long time, the basic ideas for bar code recognition were all based on zero crossing of the second derivative to detect the edges.[3,4] When the density of the bar code is low, this method can achieve a good result. However, when the bar code's density is high, if the camera's focus is not on the surface of bar codes, after convolution of the point spread function[5] of the optical system, the edges disturb each other, which causes edge locations shift.[4,5] At this time, recognition methods based on edge detection are no longer viable. So the observed data need deblurring processing before recognition. There have been some recent efforts on this problem. For example, Joseph and Pavlidis[6] calculated the standard deviation of the point spread function, and then compensated the edge locations of the bar code. In Refs. 7 and 8, the deblurring method based on deterministic expectation-maximisation algorithm was applied to process the signal. Shellhammer *et al.*[9] obtained the edges of bar code using selective sampling and edge-enhancement filter technologies. Liu and Yang[10,11] applied Fourier transform to process the observed signal to obtain the edge locations. In Ref. 12, an approach using a hidden Markov model was applied to edge detection in bar code signals. Kresic-Juric *et al.*[13,14] analysed statistical properties of edge localisation errors in bar code signals corrupted by speckle noise. Okol'nishnikova[15] applied recursive step-by-step optimisation formulas to recognize bar codes.

Although the bar code scanners are already well-established products in these days, how to deblur the

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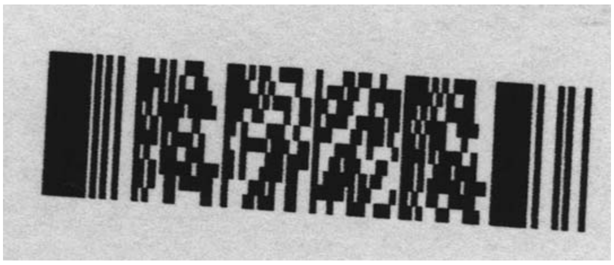


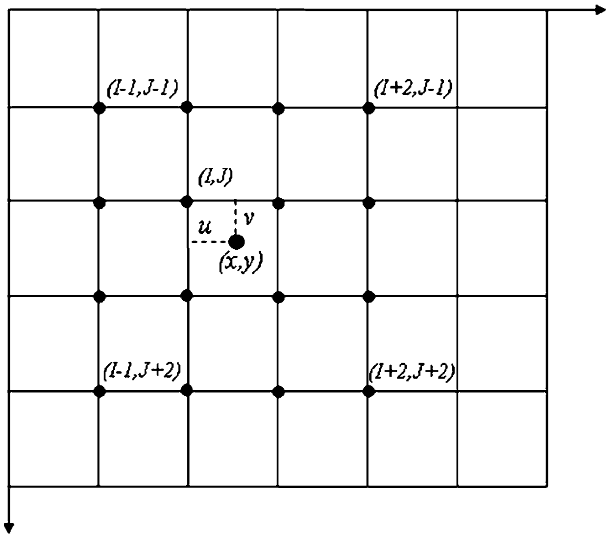
1 A tilting bar code

signal is still a hot point. It can make the scanners to recognize bar codes of higher density. Because of commercial value, the latest research is kept confidential. These existing approaches introduced before used the method of image enhance to deblur the signal, so there is limitation in deblurring range. Furthermore, most of these approaches use laser scanners to recognize stacked two-dimensional barcodes. However, with the development of barcode technology, we have to use cameras to capture images in some applications. So some new problems need to be overcome. In this paper, a novel algorithm based on iterative deconvolution is proposed to recover the signal. Under the influence of noise, the deconvolution becomes an ill-posed problem.[13] It means that a tiny change in the observed data can cause a huge change in the answers. If there are no additional assumptions or limitations, the ill-posed problem cannot be solved. After segmentation, the each row of stacked two-dimensional is composed of black bars and white spaces, so the bar code's signal is binary. Using this limitation, we present an approach based on iterative computations to process the deconvolution.

2 LOCALISATION AND SEGMENTATION

The stacked two-dimensional bar codes have similar structures. In this paper, we use PDF417[1,2] bar code as the example to present the algorithm. Bar code's localisation is an important step for recognition. The bar code needs to be located by filtering text and other signs in the image. The technology of bar code localisation can be found in Refs. 10, 11 and 16. In general, the bar code is at an angle in the image (Fig. 1). So after getting the bar code's location, it needs to rotate the bar code to be horizontal. First, the top edge points are identified, and Hough transform[17] is used to get the linear formation of bar code's top edge. The details are showed in Refs. 10, 11 and 18.

After determination of the inclination angle, the bar code needs to be rotated to be horizontal. If



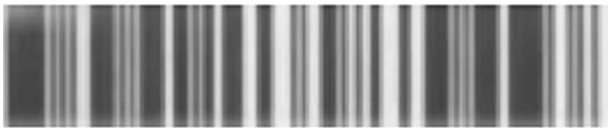
2 Interpolation of 16 points

nearest neighbour interpolation[17] is used to rotate the bar code, it will cause jagged edges. To avoid jagged edges, bilinear interpolation[17] is used in Ref. 10. However, bilinear interpolation blurs edges, so it is not suitable for deconvolution. In this paper, we use sixteen points sin $(x)/x$ interpolation.[17] It can overcome the disadvantage of jagged and blurred edges. Here, a piecewise polynomial $s(w)$ is used to approximate the best interpolation function[17] $\sin c(w)=\sin(w)/w$

$$s(w)=\begin{cases} 1-2|w|^2+|w|^3 & |w|<1 \\ 4-8|w|+5|w|^2-|w|^3 & 1\leqslant|w|\leqslant 2 \\ 0 & |w|>2 \end{cases} \quad (1)$$

As shown in Fig. 2, 16 nearby points participate in the interpolation to get the grey value of point (x,y). Here (I,J) is the nearby top-left point of (x,y) and $u=x-I$, $v=y-J$. The interpolation equation is[17]

$$\mathrm{f}(x,y)=\begin{bmatrix} s(Y_1) \\ s(Y_2) \\ s(Y_3) \\ s(Y_4) \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \mathrm{f}(I-1,J-1) & \mathrm{f}(I-1,J) & \mathrm{f}(I-1,J+1) & \mathrm{f}(I-1,J+2) \\ \mathrm{f}(I,J-1) & \mathrm{f}(I,J) & \mathrm{f}(I,J+1) & \mathrm{f}(I,J+2) \\ \mathrm{f}(I+1,J-1) & \mathrm{f}(I+1,J) & \mathrm{f}(I+1,J+1) & \mathrm{f}(I+1,J+2) \\ \mathrm{f}(I+2,J-1) & \mathrm{f}(I+2,J) & \mathrm{f}(I+2,J+1) & \mathrm{f}(I+2,J+2) \end{bmatrix} \begin{bmatrix} s(X_1) \\ s(X_2) \\ s(X_3) \\ s(X_4) \end{bmatrix} \quad (2)$$



3 The image of a row of bar code

where

$$X_1 = 1+u,\ X_2 = u,\ X_3 = 1-u,\ X_4 = 2-u$$
$$Y_1 = 1+v,\ Y_2 = v,\ Y_3 = 1-v,\ Y_4 = 2-v \tag{3}$$

and $s(X_i)$ and $s(Y_i)$ (i=1, 2, 3, 4) are obtained from equation (1). This interpolation has high precision and can maintain the image edge detail better. It is especially useful in the recognition of high density bar codes. Then we use the boundary locations between the rows to segment the whole bar code into rows before recognition. After segmentation, the image of each row of the bar code is obtained (Fig. 3).

3 THE MODEL OF BAR CODE'S SIGNAL

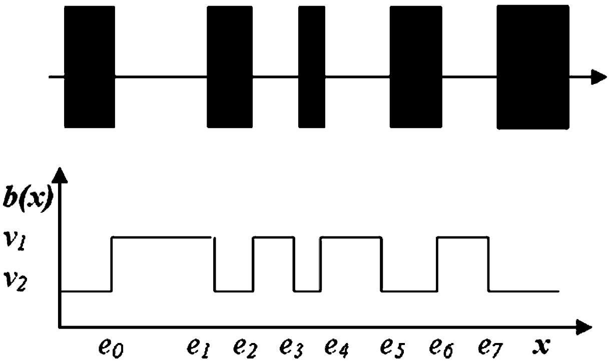
Here the model of the bar code's signal is first introduced. For more details, please refer to Refs. 4 and 8. We assume that the grey value of bar code's white space is v_1 and the grey value of black bar is v_2 after capture. Using a horizontal line to scan the bar code, a wave can be obtained (Fig. 4).

If the edge locations of the bar code are e_i (i=0, 1, …, $n-1$), the ideal signal in Fig. 4 can be expressed using the function[6]

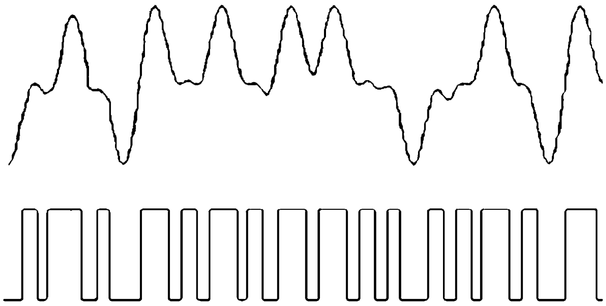
$$b_{\mathrm{ideal}}(x) = \sum_{i=0}^{n-1} \left[(-1)^i (v_1 - v_2) U(x-e_i)\right] + v_2 \tag{4}$$

where $U(x)$ is the step function

$$U(x) = \begin{cases} 1 & x \geqslant 0 \\ 0 & x < 0 \end{cases} \tag{5}$$



4 The bar code's signal



5 The signal after convolution

Without loss of generality, we can set v_1=1 and v_2=0. Considering the random noise $n(x)$, equation (4) can be expressed as

$$b_{\mathrm{noise}}(x) = \sum_{i=0}^{n-1} \left[(-1)^i U(x-e_i)\right] + n(x) \tag{6}$$

In order to reduce the noise, we take advantage of the bar code's two-dimensional character. We calculate the bar code vertical projection signal to improve signal-to-noise ratio. In this way, random noise can be presented as a two-dimensional function $n(x,y)$. We can assume that the average value of the random noise is 0, and the signal of the random noise can be ignored after projection. Thus, the equation above can be presented as

$$\begin{aligned} b(x) &= \frac{1}{H}\sum_{y=0}^{H-1}\left\{\sum_{i=0}^{n-1}\left[(-1)^i U(x-e_i)\right] + n(x,y)\right\} \\ &= \sum_{i=0}^{n-1}\left[(-1)^i U(x-e_i)\right] + \frac{1}{H}\sum_{y=0}^{H-1} n(x,y) \\ &= \sum_{i=0}^{n-1}\left[(-1)^i U(x-e_i)\right] \end{aligned} \tag{7}$$

where H is the bar code's height.

A typical image collection system consists of a light source and an optical sensor.[19] The light source is used to generate a light point, and the optical sensor is use to collect the reflection light and to produce a signal. Because the light point has a certain physical size, the actual signal $w(x)$ obtained though optical system is the convolution of the light point's point spread function (PSF) $g_{\mathrm{PSF}}(x)$ and $b(x)$

$$w(x) = g_{\mathrm{PSF}}(x) b(x) = \sum_{i=0}^{n-1}\left[(-1)^i g_{\mathrm{PSF}} U(x-e_i)\right] \tag{8}$$

In optical systems, $g_{\mathrm{PSF}}(x)$ is a Gaussian function[6,19]

$$g_{\mathrm{PSF}}(x) = \frac{1}{(2\pi)^{1/2}\sigma}\exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{9}$$

where σ is a standard deviation of the PSF and σ is determined by the size of light beam and the distance between light head and bar code. After convolution, the edges of the bar code will shift, or even disappear (Fig. 5). So we need deconvolve the signal before recognition.

4 SYSTEM IDENTIFICATION

Before deconvolution, we need to know the form of the PSF of the optical system, so we need to obtain σ by analysing $w(x)$. From the definition, it is easy to know the first derivative of $g_{\mathrm{PSF}}(x)$

$$g'_{\mathrm{PSF}}(x) = -\frac{x}{(2\pi)^{1/2}\sigma^3}\exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (10)$$

The first derivative of $w(x)$ is

$$w'(x) = \sum_{\mathrm{i}=0}^{\mathrm{n}-1}\left[(-1)^{\mathrm{i}} g_{\mathrm{PSF}}(x-e_{\mathrm{i}})\right] \quad (11)$$

and its second derivative is

$$w''(x) = \sum_{\mathrm{i}=0}^{\mathrm{n}-1}\left[(-1)^{\mathrm{i}} g'_{\mathrm{PSF}}(x-e_i)\right] \quad (12)$$

From equations (9) and (10), we can conclude $\lim_{x\to\infty} g_{\mathrm{PSF}}(x)=0$ and $\lim_{x\to\infty} g'_{\mathrm{PSF}}(x)=0$. Thus, we can approximate them to $g(x)$ and $g'(x)$ as below

$$g(x) = \begin{cases} \frac{1}{(2\pi)^{1/2}\sigma}\exp\left(-\frac{x^2}{2\sigma^2}\right) & |x| \leqslant T \\ 0 & |\mathrm{x}| > T \end{cases} \quad (13)$$

$$g'(x) = \begin{cases} -\frac{x}{(2\pi)^{1/2}\sigma^3}\exp\left(-\frac{x^2}{2\sigma^2}\right) & |\mathrm{x}| \leqslant T \\ 0 & |\mathrm{x}| > T \end{cases} \quad (14)$$

where T is the threshold. In general, it can be set to 3σ.

Considering a boundary e_{j}, if the distance between itself and its nearest boundary is larger than T, we call this boundary isolated boundary. As for an isolated boundary, there are two propositions.

Proposition 1. If e_{j} is an isolated boundary, $\sigma = 1\big/(2\pi)^{1/2}\left|w'(e_{\mathrm{j}})\right|$.

Proof.

From equations (11) and (13), we can know that the first derivative of $w(x)$ at an isolated boundary e_{j} is

$$\left|w'(e_{\mathrm{j}})\right| = \left|\sum_{\mathrm{i}=0}^{\mathrm{n}-1}\left[(-1)^{\mathrm{i}} g(e_{\mathrm{j}}-e_{\mathrm{i}})\right]\right| \quad (15)$$

Since e_{j} is an isolated boundary, $\left|e_{\mathrm{i}}-e_{\mathrm{j}}\right| > T$, $\forall i \neq j$.

From equation (13), we know that $g(e_{\mathrm{j}}-e_{\mathrm{i}})=0$, $\forall i \neq j$, so

$$\left|w'(e_{\mathrm{j}})\right| = |g(0)| = \frac{1}{(2\pi)^{1/2}\sigma} \quad (16)$$

That is

$$\sigma = \frac{1}{(2\pi)^{1/2}\left|w'(e_{\mathrm{j}})\right|} \quad (17)$$

Proof finished.

Proposition 2. If e_{j} is an isolated boundary, $w''(e_{\mathrm{j}})=0$.

Proof.

From equations (12) and (14), we can know the second derivative of $w(x)$ at e_{j}

$$w''(e_{\mathrm{j}}) = \sum_{\mathrm{i}=0}^{\mathrm{n}-1}\left[(-1)^{\mathrm{i}} g'(e_{\mathrm{j}}-e_{\mathrm{i}})\right] \quad (18)$$

Because e_{j} is an isolated boundary, $\left|e_{\mathrm{i}}-e_{\mathrm{j}}\right| > T$, $\forall i \neq j$.

From equation (14), $g'(e_{\mathrm{j}}-e_{\mathrm{i}})=0$, $\forall i \neq j$, so

$$w''(e_{\mathrm{j}}) = (-1)^{\mathrm{j}} g'(0) = 0 \quad (19)$$

Proof finished.

From Propositions 1 and 2, we know that for an isolated boundary, its second derivative is 0. With this principle, we can calculate the second derivative of the signal and find out the point where the second derivative is 0. Then we locate the isolated boundary and use equation (17) to get σ.

5 DECONVOLUTION BASED ON ITERATIVE COMPUTATIONS

In the actual capture, the waveform $w(x)$ is a discrete sequence, and equation (8) is expressed as a discrete form

$$w_{\mathrm{discrete}}(x) = \sum_{\mathrm{i}} g(i)b(x-i) \quad (20)$$

Assuming that in the discrete form, there are L observed data points, $w_0, w_1, \ldots, w_{\mathrm{L}-1}$, and the length of $g(x)$ is M. From the definition of convolution, we can conclude that there are $M+L-1$ original data points, $b_0, b_1, \ldots, b_{\mathrm{M+L}-2}$ participating in the convolution. Then equation (8) is expressed as a matrix form

$$\begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ \vdots \\ w_{L-1} \end{bmatrix} = \begin{bmatrix} g_{M-1} & g_{M-2} & \cdots & g_0 & & & & \\ & \ddots & & & \ddots & & & \\ & & g_{M-1} & g_{M-2} & \cdots & g_0 & & \\ & & & \ddots & & & \ddots & \\ & & & & g_{M-1} & g_{M-2} & \cdots & g_0 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ \vdots \\ b_{M+L-2} \end{bmatrix} \quad (21)$$

Now we have the observed data w_0, w_1, …, w_{L-1} and g_0, g_1, …, g_{M-1}. In theory, if we have some initial values, solving a set of linear equations from equation (21) can complete the deconvolution processing and obtain the original data b_0, b_1, …, b_{M+L-2}. However, in fact, deconvolution is a type of inverse problem. An important character of inverse problem is ill-posed.[4,6] The meaning of an ill-posed equation is that its solution does not continuously depend on the observed data. In other words, a tiny change in the observed data can cause a huge change in the solution. In the case of the linear equations from equation (21), it is impossible to avoid noise while capturing w_0, w_1, …, w_{L-1}, which will cause a change in the values of w_0, w_1, …, w_{L-1}. A tiny change of w_0, w_1, …, w_{L-1} can cause a huge change in b_0, b_1, …, b_{M+L-2}, so solving the linear equations from equation (21) directly cannot obtain the original data.

Without additional assumptions or limitations, ill-posed problem cannot be solved.[5] However, the deconvolution processing of a bar code is a specific problem. A bar code signal has two propositions as noted as below:

Proposition 3. A bar code is composed of black bars and white spaces, so the bar code signal is binary, which is 0 or 1.

Proposition 4. A bar code has quiet zone.[1] In the quiet zone, the value of bar code signal is 1.

Under these two propositions' limitations, we can use an iterative method to solve the set of linear equations in equation (21). Considering the first equation in the set of linear equations

$$w_0 = g_{M-1}b_0 + \ldots + g_1 b_{M-2} + g_0 b_{M-1} \quad (22)$$

We can obtain

$$b_{M-1} = \frac{w_0 - (g_{M-1}b_0 + g_{M-2}b_1 + \ldots + g_1 b_{M-2})}{g_0} \quad (23)$$

In the actual capturing, it is easy to make sure that the captured data include the quiet zone of the bar code. From Proposition 4, we can conclude that in bar code's quiet zone, the value of the bar code's signal is 1, which means

$$b_0 = b_1 = \ldots = b_{M-2} = 1 \quad (24)$$

From the equations above, we can obtain the value of b_{M-1}. Considering the noise, a tiny change of observed data will cause a huge change in the signal. Hence, the method of equation (23) is quite noise sensitive. So we have to regularize the value of b_{M-1} as below

$$b_{M-1} = \begin{cases} 0 & b_{M-1} < 0 \\ b_{M-1} & 0 \leqslant b_{M-1} \leqslant 1 \\ 1 & b_{M-1} > 1 \end{cases} \quad (25)$$

Using the iterative computation in this way, from the $(i+1)$th equation in the set of linear equations

$$w_i = g_{M-1}b_i + \ldots + g_1 b_{i+M-2} + g_0 b_{i+M-1} \quad (26)$$

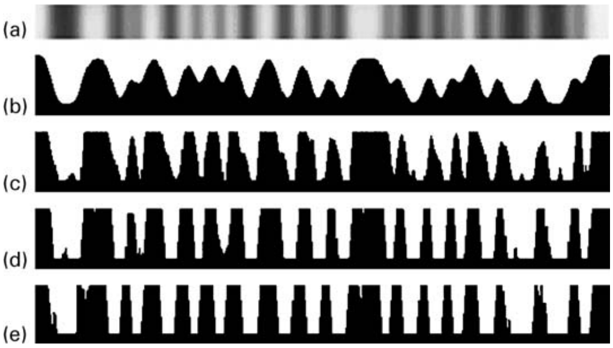
we can obtain

$$b_{i+M-1} = \frac{w_i - (g_{M-1}b_i + g_{M-2}b_{i+1} + \ldots + g_1 b_{i+M-2})}{g_0} \quad (27)$$

Then we regularize the value of b_{i+M-1} as the way in equation (25). In this iterative method, we can obtain all of the original data and then decode them to get the information in the bar code.[1,10]

We know the tails of the PSF approach zero. After that, we locate the isolated boundary and use equation (17) to get σ. In actual deconvolution computation, we use the threshold T to cut off the tails of it as equation (14) expresses.

Figure 6 shows the deconvolution results for various values of the threshold T. In Fig. 6c, $T=2\sigma$, which results in a considerable part of the PSF being set to zero. This causes the signal after deconvolution is still blurring. In Fig. 6d, $T=3\sigma$, and we can see that after the deconvolution, the recovered signal has a better effect. In Fig. 6e, $T=3.5\sigma$, and the deconvolution effect is also good, but there is some disturbance in the signal. This is mainly because the value of the PSF far away from zero is very small. Thus, a tiny



6 (a) A row of blurred bar code; (b) the projection signal of the row of the bar code; (c) the deconvolution result when $T=2\sigma$; (d) the deconvolution result when $T=3\sigma$; (e) the deconvolution result when $T=3.5\sigma$

change can cause the disturbance in the signal. Although we use equation (25) to regularize the value during deconvolution, this disturbance cannot be completely avoided. Usually, setting $T=2.5\sigma$–3σ can obtain a perfect deconvolution effect, without signal disturbance.

6 EXPERIMENTAL RESULTS

6.1 Blurring range

According to the above analysis, we know that the standard deviation σ is an important factor in the algorithm. If its value is big, the signal will be severely blurred. In this subsection, we will test the recognition rates for various values of σ. First, 400 PDF417 bar codes are generated randomly and a Gaussian PSF is applied to blur these bar codes. Then, we print and scan them. In the experiment, we recognize them using the algorithm proposed in this paper. This experiment is repeated for several values of σ. The results are given in Table 1 (where W is the module's width).[1]

In Ref. 6, the maximum value of σ/W that can be allowed is 0.5, and when σ/W is 1.25, the recognition rate is nearly zero. From the data in Table 1, we can see that the algorithm in this paper still has good performance when σ increases. Furthermore, when σ/W is 1.25, we can get a recognition rate of 76.75%. Because the algorithm in this paper is based on the strategy of signal recovery, not the strategy of signal enhancement, it can process more blurred signals.

Table 1 The recognition rate for various blurring factors

σ/W	Recognition rate (%)
0.25	99
0.5	93.5
0.75	90.5
1.0	88.5
1.25	76.75

6.2 Noise immunity

In this subsection, we verify that the algorithm is robust in the presence of noise. We add noise to 400 PDF417 bar codes images, and then recognize them with the algorithm based on iterative deconvolution. The module's width of PDF417 bar codes is 7/300 inch (about 23 miles). The Metrologic IS4920 image engine is used to capture images. Its camera is with the resolution of 1280 × 960 pixels. And this engine uses 650 nm light source for illumination. The focal point of engine is 100 mm from the image's surface. In the experiment, the distance between camera and surface of bar codes is set to 250 mm, so the images captured become blurring.

Two typically forms of noise are tested in this experiment. One is salt and pepper noise.[17] This experiment is repeated for several various signal-to-noise ratios, and the results are given in Table 2. Another form of noise is Gaussian noise.[17] Here the mean of the noise is set to zero. And this experiment is repeated for several various values of standard deviation of Gaussian distribution. The results are given in Table 3.

From the data in Tables 2 and 3, we can see that the algorithm proposed in this paper has good noise immunity. This is because we apply two effective strategies to reduce the noise in the algorithm. First,

Table 2 The recognition rate for various salt and pepper noise factors

Noise ratio	Recognition rate (%)
0.05	99.5
0.1	98.75
0.15	89.25
0.2	79

Table 3 The recognition rate for various Gaussian noise factors

Standard deviation	Recognition rate (%)
20	100
40	97.25
60	93.5
80	83

we use equation (7) to calculate bar code's vertical projection signal. This can improve the signal-to-noise ratio greatly. Second, we use equation (25) to regularize the signal after each step in deconvolution.

6.3 Comparison of algorithms

In this subsection, we compare the performance of three kinds of recognition algorithm. The first is the algorithm based on the traditional edge detection algorithm based on zero crossing of the second derivative. The second is Fourier transform in Ref. 10. In these two kinds of algorithm, bilinear interpolation is used to rotate images. The third is the algorithm based on iterative deconvolution proposed in this paper. In this algorithm, we test bilinear interpolation and sin $(x)/x$ interpolation to rotate images respectively.

In the experiment, 400 PDF417 bar codes with different module widths are generated randomly and then printed. Among them, the minimal module's width is 4/300 inch (about 13 miles) and the maximum module's width is 7/300 inch (about 23 miles). We also use Metrologic IS4920 image engine to capture images. The focal point of engine is 100 mm from the image's surface. In the experiment, the distance between camera and surface of bar codes is set to 250 mm. Differing from the scanner, the camera is a kind of off-touch capture device, and the distance between the camera and the bar code is far. So its PSF causes a more severe blurring effect than scanner. This experiment is repeated for various values of module width. The results are given in Table 4.

From Table 4, we can see that the performance of the algorithm based on Fourier transform is superior to the traditional algorithm based on edge detection. However, with increasing bar code density, the performance of the algorithm based on Fourier transform deteriorates dramatically too. At the same time, the recognition algorithm based on iterative deconvolution still has a high recognition rate and outstanding performance. This algorithm applies the iterative method to processing the deconvolution and it can recover the original data effectively. Furthermore, by comparing the data of columns 3 and 4 in the table, we can know that sin $(x)/x$ interpolation of 16 points can overcome the disadvantage of bilinear interpolation and get a higher recognition rate.

7 CONCLUSION

Accurate edge localisation is of primary importance in the recognition of bar codes. However, after the convolution of the PSF of the optical system, the edges of the bar code will shift, or even disappear. Thus, it is necessary to process the signal before edge detection. In this paper, we present a novel solution based on iterative deconvolution. Deconvolution is an inverse problem, which cannot be solved without additional limitations. The signal of the bar code is binary. With this limitation, we use the strategy of iterative computations to process signal. The experiments show that the algorithm based on iterative computations has good performance. It can process more blurred signals than previous models.

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Table 4 Recognition rate of three kinds of algorithm

	Recognition rate			
Module width (1/300 inch)	Edge detection (%)	Fourier Transform (%)	Iterative deconvolution with bilinear interpolation (%)	Iterative deconvolution with sin $(x)/x$ interpolation (%)
4	24.5	75.25	88.25	94.25
5	52.25	88.5	90.5	95.5
6	62.75	96.25	95.25	97.25
7	91.5	100	100	100

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