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AUTOMATIC LOCATION FOR MULTI-SYMBOLOGY AND MULTIPLE 1D AND 2D BARCODES

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Key words: multi-symbology, 1D and 2D barcode location, modified run length smearing algorithm.

ABSTRACT

Multi-symbology barcode location is a practical and challenging issue. Image-based barcode recognition techniques are robust and extendable approaches for reading versatile one-dimensional (1D) and two-dimensional (2D) barcodes. Most methods may work for a single 1D or 2D barcode or rely on a unique pattern to locate a single 1D or 2D barcode. This work proposes a general localization framework for extraction of real barcodes under complex backgrounds when multiple symbology types exist in the same snapshot for 1D barcodes, 2D barcodes, or both. There are five steps of the proposed algorithm: image grayscale conversion, adaptive thresholding, application of a modified run length smearing algorithm, connected-component labeling, and barcode verification. Experimental results indicate that the proposed approach can locate multiple barcodes and multi-symbology barcodes in complex backgrounds with acceptable accuracy.

I. INTRODUCTION

Barcode technology has been applied widely to, say, daily goods, industrial products, pharmacy descriptions, automatic identification, inventory inspections, postal services, library management, and banking systems [13, 14, 18, 21]. Two barcode symbology types, the one-dimensional (1D) barcode and two-dimensional (2D) barcode, are standard methods for representing data. The 1D barcode consists of black and white collateral lines of different widths. However, different 2D symbols have their own morphological structure: stacked linear bars (e.g., PDF417 and Codablock), and contain special patterns, such as that of Data Matrix, Quick Response (QR) code and Aztec code. The 2D barcode methodology has advantages over linear barcodes in terms of their ability to store large amounts of information and robust error correction capability. In Japan, the QR code has been widely used to exchange messages in daily life. The Taiwan High Speed Rail system uses a QR code on train tickets to prevent the use of fake tickets. The PDF417 barcode is utilized by the Taiwan's Ministry of Finance for income tax records. Additionally, 2D barcodes are now deployed extensively by several tagging systems in the life sciences, and for agricultural product portfolios, semiconductors, and electronic products.

Laser barcode scanners are commonly used to read 1D barcodes. However, laser barcode scanners can only read one barcode at a time. The image-based barcode scanner is relatively more practical and has many advantages over laser scanners. For instance, an image-based barcode system can read multiple 1D and 2D barcodes simultaneously.

Many image-based methods for barcode identification have been developed. Gallo and Manduchi developed a new image-based 1D barcode decoding approach which utilizes deformable templates to represent barcode digits and reduces errors with global spatial coherence [7]. Chen *et al*. generated a two-stage approach that connects the contours of an orientation-based region and locating the contour-connected component-based target, to segment a diversified barcode [4]. Zhang *et al*. developed another two-stage approach with two down-sampled resolutions, in which the barcode is identified by region-based analysis [23]. Chandler and Batterman developed an omnidirectional barcode reader that computes the accumulated sum of the products of derivatives of the first and second lines to locate the barcode image, and then calculates the cross-correlation of interpolated scan line data to acquire the orientation of the located barcode [3]. Fang *et al*. applied a projection method to extract linear code (code-39) features for recognition [6]. Ando and Hontani extended their feature extraction method to extract and read barcodes in 3D scenes using categorization and projection for edges, ridges, corners and vertices [1]. Ouaviani *et al*. adopted some image processing techniques to segment some of the most common 2D barcodes, including the QR code, Maxicode, Data Matrix, and PDF417 [16]. Hu *et al*. developed a 2D barcode extraction

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system based on texture direction analysis [9]. Chin *et al*. used integral images to detect 2D barcodes at generic angles [5]. Liang *et al*. combined three-stage image processing algorithms to segment a barcode from an original image with adequate accuracy [10]. Zafar *et al*. utilized two software tools to detect and decode multiple Data Matrix barcodes [22]. Xu and McCloskey focused on solving the localization and de-blurring problem of motion-blurred 2D bar codes using corner feature and motion direction estimation [20].

Most other techniques in literature work for single 1D or 2D barcode, and rely on finding the unique pattern, or are based on naïve assumptions as known code type or start location. Our previous study focuses on 1D barcode recognition and achieved satisfactory segmentation performance [12]. Extended from our preliminary investigation [11], this work proposes a novel location framework that determines the location of barcodes under complex background when multiple symbology types appear in the same snapshot for 1D barcodes, 2D barcodes, or both. The remainder of this paper is organized as follows. Section 2 describes in detail the issues involved in automatic barcode location procedure of the proposed system. Section 3 presents experimental results. Section 4 gives conclusions and directions for future works.

II. AUTOMATIC BARCODE LOCALIZATION

The proposed system uses some image processing methods to locate barcodes from an image. Fig. 1 shows the flowchart of the proposed barcode location system. Firstly, an input image is converted into a grayscale image. Second, to remove undesired pixels, adaptive thresholding is applied. The modified run length smearing algorithm (mod-RLSA) is then used to gather pixels near interesting pixels. After the congregated region is acquired, connected component labeling is applied to mark different regions. Finally, this system determines whether a region is a barcode.

1. Grayscale Conversion

An input image may contain such objects as text, logos, and lines. Furthermore, 1D and 2D barcodes may exist in the same image (Fig. 2). This work first applies Eq. (1) to generate a grayscale image *G*, which is used as a measure of overall brightness or luminance.

$$G(x, y) = 0.299 \times r(x, y) + 0.587 \times g(x, y) + 0.114 \times b(x, y) \quad (1)$$

where *r*, *g*, and *b* represent red, green, and blue channels in an image, respectively. Via this operation, the input image is converted into a grayscale image. Fig. 3 shows the result of applying the grayscale transformation to an input barcode image (Fig. 2).

2. Adaptive Thresholding

After the grayscale image is acquired, adaptive thresholding is applied to remove pixels with high luminance and retains pixels with low luminance. Many adaptive thresholding methods, such as Ostu's method [15], the Iterative Selection Thresholding method [17], and the Balanced Histogram Thresholding (BHT) method [2], have been developed. These methods generate perfect threshold results. However, the computation complexity is high. Thus, this is work does not use these methods. This work first applies the following procedure to find a threshold *T* [8]:

step 1: Select an initial value for T.
step 2: Using T to segment an image. This will produce two groups of pixels: G_1 contains all pixels with grayscale values > T and G_2 contains pixels with value ≤ T.
step 3: Compute average values T_1 and T_2 for G_1 and G_2, respectively.
step 4: Compute a new threshold value $T = (T_1 + T_2) / 2$.
step 5: Repeat steps 2-4 until the difference between new threshold value T and original threshold value is smaller than a predefined value T_0 in successive iterations.

This method is relatively simple and robust against noise. After a threshold *T* is acquired, Eq. (2) is applied to retain desired pixels.

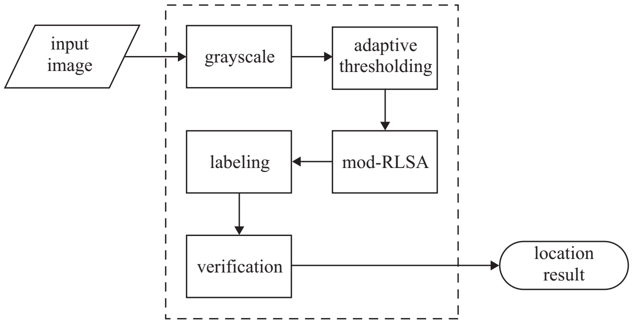


Fig. 1. Flowchart of the proposed barcode location framework.


Fig. 2. The input image captured by a CCD camera containing versatile 1D and 2D barcodes.


Fig. 3. The grayscale image generated by grayscale conversion.

Fig. 4. The binary image produced by applying adaptive thresholding.

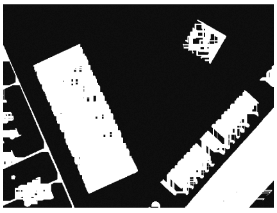


Fig. 5. The outcome of applying mod-RLSA to the binary image (Fig. 4).

$$B(x,y)=\begin{cases}1 & \text{, if } G(x,y)\le T\\ 0 & \text{, otherwise}\end{cases} \tag{2}$$

Fig. 4 shows the outcome of applying the adaptive thresholding to the grayscale image in Fig. 3.

3. The Modified Run Length Smearing Algorithm (mod-RLSA)

According to [19], the proposed mod-RLSA is applied to locate a block region and a text area. The proposed mod-RLSA is as follows.

step 1: Convert pixels of a binary image by applying the following rules to each row. Image R_1 is then obtained.
- Change 0s to 1s if the number of adjacent 0s is less than or equal to a predefined value C.
- 1s are unchanged.

step 2: Convert image information using the rules in step 1 for each column. Image R_2 is then obtained.

step 3: Apply Eq. (3) to combine R_1 and R_2.

$$R(x,y)=\begin{cases}1, & \text{if } R_1(x,y)=1 \text{ and } R_2(x,y)=1\\ 0, & \text{otherwise}\end{cases} \tag{3}$$

However, Eq. (4) is substituted for Eq. (3) in the last step of mod-RLSA to increase the accuracy in location the barcode.

$$R(x,y)=\begin{cases}1, & \text{if } R_1(x,y)=1 \text{ or } R_2(x,y)=1\\ 0, & \text{otherwise}\end{cases} \tag{4}$$

After the mod-RLSA is applied, the barcode region is obviously smeared (Fig. 5).

4. Connected-component Labeling

Instead of using a conventional progressive approach for connected-component labeling, this work applies an array to deal with the equivalent label, as shown in Algorithm 1 where **f(row, col)** denotes the grayscale value of image pixel at coordinates **(row, col)** and **r(row, col)** denotes the result of labeling of the corresponding image pixel at coordinates **(row, col)**. Pass one records equivalent labels and assigns temporary labels. Pass two replaces each temporary label by its equivalent label from the equivalent label list.

Algorithm 1: The Connected-Component Labeling Algorithm

```
Create an equivalent list L[]
Label = 0
NumComponent = 0
// pass one
for row = 1 to height do
 for col = 1 to width do
  if f(row, col) is not background then
   if f(row-1, col) and f(row, col-1) are
    background then
    Label += 1;
    r(row, col) = Label;
    L[Label] = Label;
   else if f(row-1, col) is background then
    r(row, col) = r(row, col-1);
   else if f(row, col-1) is background then
    r(row, col) = r(row-1, col);
   else
    m = min(r(row-1, col), r(row, col-1));
    r[row][col] = m;
    L[max(r(row-1, col), r(row, col-1))] = m;
   end if
  end if
 end for
end for
// process the equivalent list
for index = 1 to Label do
 if L[index] == NumComponent then
  NumComponent += 1;
  L[index] = NumComponent;
 else
  L[index] = L[L[index]];
 end if
end for
// pass two
for row = 1 to height do
 for col = 1 to width do
  r(row, col) = L[r(row, col)];
 end for
end for
```

5. Barcode Verification

When a potential barcode is detected, it must be differenttiated from background clutter. Identifying real barcodes

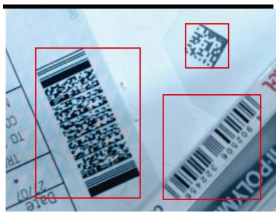


Fig. 6. The location result by the proposed system for the test image in Fig. 2.

effectively is important to avoid false-positive results. This work classifies the candidate barcode according to following conditions.

- Total number of pixels in a region exceeds 300.
- The width of a region is ≤ 512 and its height ≤ 384.

These conditions can be applied to verify that the candidate barcode is a real barcode. The proposed system can achieve multiple omnidirectional barcodes location in the example barcode image (Fig. 2). Fig. 6 shows the location result by the proposed system for the test image.

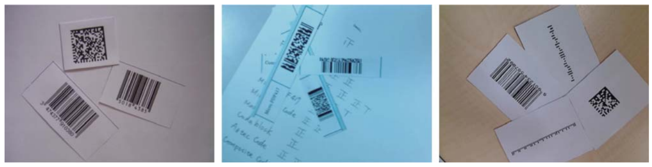
III. EXPERIMENTAL RESULTS

Experiments were performed on an image with a mixture of 1D and 2D barcodes. Multiple symbology types were tested, including ten 1D barcode types–13-digit European Article Number (EAN-13), EAN-8, Universal Product Code version A (UPC-A), UPC-E, Code 39, Code 128 Interleaved 2 of 5 (ITF), United States Postal Service Postal Numeric Encoding Technique (USPS POSTNET), Royal Mail 4-state Customer Code, and USPS Intelligent Mail, and nine 2D barcode types–Portable Data File (PDF417), Data Matrix, QR Code, Micro PDF417, Micro QR Code, MaxiCode, Codablock, Aztec Code, and Composite Code. This work utilized Sony DSC-P10 auto-focus digital camera to capture several barcode types with Video Graphics Array (VGA) resolution of 640 by 480. The distance between the camera and barcodes was not fixed. In total, 662 images of various objects contain 485 1D barcodes and 492 2D barcodes with complex backgrounds. Fig. 7 shows some example test images. Figs. 8(a)-(c) show barcode location results for these input images in Figs. 7(a)-(c), respectively.

The previous study focuses on single type (1D) barcode recognition and has achieved satisfactory segmentation performance [12]. Table 1 shows experimental results by the proposed method and compares these results with those obtained by Chen *et al.* [4] and Zhang *et al.* [23]. The previously proposed framework works well for pure 1D barcodes segmentation and achieves 95.62% correct segmentation rate. The proposed system outperforms those methods and has significantly fewer false-positive locations. This work focuses on locating multi-symbology barcodes, i.e., 1D and 2D barcodes may co-exist within the same image. The 1D barcodes have many parallel lines; however, 2D barcodes do not. Thus,

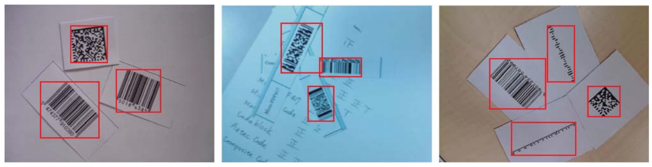
Table 1. Correct extraction rate of proposed method, and that of methods developed by Chen *et al.* and Zhange *et al.*, each of which was applied to various images with multiple barcodes [12].

Code type	# of barcode	Proposed method	Chen *et al.* [4]	Zhange *et al.* [23]
Code 39	56	100%	96.43%	94.96%
I25	47	95.74%	93.62%	91.49%
UPC-E	61	95.08%	93.44%	85.25%
UPC-A	43	95.35%	90.70%	83.72%
EAN-8	70	91.43%	90.00%	72.86%
EAN-13	55	98.18%	94.55%	76.36%
Code 128	56	94.64%	91.07%	83.93%
Overall	388	95.62%	92.78%	83.51%



(a) (b) (c)

Fig. 7. Some example barcode test images.



(a) (b) (c)

Fig. 8. Barcode location results of test images in Fig. 7 (a)-(c), respectively.

locating 1D and 2D barcodes simultaneously is challenging. This work tested 2,501 images; each image may contain different numbers of 1D and 2D barcodes. Although this location task is difficult, the proposed method still achieves an acceptable correct locate rate. Tables 2 and 3 list the experimental results of each barcode type in test images. For the 1D barcodes, the proposed system achieves superior performance of 95.88% correct locate rate; the average correct locate rate is 94.35% for 2D barcodes. The results demonstrate that the proposed system improves our previous studies [11, 12]. Our 1D barcode segmentation performance outperforms the methods developed by Chen *et al.* and Zhang *et al.* [4, 23]. For 2D barcode localization, our approach performs a little less than that of Chen *et al.* in PDF417 symbols (91.04% *vs.* 98.7%). However, Chen's system was tested only on three barcode symbols (Code39, Data Matrix and PDF417) [4]. Furthermore, the proposed algorithm is robust and is capable of simultaneously extracting more than 19 types of popular commercial symbologies, including traditional 1D bar codes, post codes, stacked bar codes and 2D matrix symbologies.

Table 2. Correct locate rate of 2,111 1D barcodes in test images.

code type	# of barcode	# of correct locate	correct locate rate
Code 39	238	221	92.86%
Code 128	56	50	89.29%
EAN-8	62	57	91.94%
EAN13	192	169	88.02%
UPC-A	46	42	91.30%
UPC-E	62	55	88.71%
I25	47	45	95.74%
POSTNET	681	677	99.41%
RM4SCC	327	308	94.19%
Intelligent Mail	400	400	100.00%
overall	2111	2024	95.88%

Table 3. Correct locate rate of 744 2D barcodes in test images.

code type	# of barcode	# of correct locate	correct locate rate
PDF417	67	61	91.04%
Data Matrix	172	168	97.67%
QR Code	201	194	96.52%
Micro PDF417	55	54	98.18%
Micro QR Code	62	58	93.55%
Maxicode	42	38	90.48%
Codablock	48	41	85.42%
Aztec Code	51	45	88.24%
Composite Code	46	43	93.48%
Overall	744	702	94.35%

The system is also enabled with omnidirectional processing of all bar codes.

IV. CONCLUSION

This study proposes a novel general location framework to extract for real barcodes from images with complex backgrounds, especially when multiple symbology types, 1D barcode, 2D barcodes or both, exist in the same snapshot. The proposed method has five steps: image grayscale conversion, adaptive thresholding, application of mod-RLSA, connected-component labeling, and barcode verification. Experimental results indicate that the proposed framework has an acceptable accurate locate rate.

Notably some tasks can be improved. To improve location performance, one can review incorrect location cases and revise the barcode verification approach. Additionally, the proposed system will be tested on variant barcode sizes. Furthermore, the decoding mechanism for 2D barcodes will be developed further to improve the location method.

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