Morphological Segmentation of 2-D Barcode Gray Scale Image

Jian-Hua Li [1, a]
Key Laboratory of Electronic Thin Films and Integrated Devices University of Electronic Science and Technology of China, Chengdu China 610054
Jianhua703@163.com

Yi-Wen Wang [a], Yi Chen [b], Meng Zhang [c], Guo-Cheng Wang [d], Ping Li [e]
Key Laboratory of Electronic Thin Films and Integrated Devices University of Electronic Science and Technology of China, Chengdu China 610054
[a]yiwen@uestc.edu.cn [b]chenyi261@gmail.com [c]zm486153@yahoo.com.cn [d]wgch19890113@163.com

***Abstract*—Segmentation is a key process of 2-D barcode identification. In this paper we propose two 2-D barcode image segmentation algorithms under complex background. The first algorithm is an expansion of multi-scale morphology reconstruction and it can acquire a good segmentation result. However, this algorithm is not suitable for fast real-time image processing due to large computation. To fix the shortcoming of the first algorithm we put forward a fast real-time image segmentation algorithm. The proposed approach is applied in experiments on 2D barcodes with complicated background. In experiments, the second proposed method can maintain image segmentation accuracy while significantly reducing the time consumption.**

***Index Terms*— mathematical morphology, morphological segmentation, reconstruction, structure element.**

I. Introduction

Among the wide range of automatic identifications such as RFID, magnetic card, barcode is becoming increasingly popular in recent years. Barcode technique was first introduced by Westing house Lab in 1920s. It is a symbol composed by bars and blanks according to a certain encoding rule, and it can store numbers and letters in a small space [1]. There are two basic types of barcode: 1-D and 2-D. 1-D barcode stores information only in horizontal direction. While 2-D barcode stores information in both the horizontal and vertical directions using organized blanks and bars, so 2-D barcode effectively solved defects such as low information capability, low information density, poor stability and safety that exist in 1-D barcode [2-5]. Therefore, 2-D barcode is attracting more and more attention from research to industry community, such as electronic tickets, product labels and so on [6].

The key point to 2-D barcode identification lies in the processing of barcode image. Images acquired by camera often contain a lot of complex backgrounds in addition to barcode. These complex backgrounds bring great challenges to 2-D barcode identification. In order to get a high barcode identification rate, we must extract code image from complex backgrounds.

2-D barcode image segmentation technique has always being receiving great attention in recently decades and a lot of segmentation algorithms have been proposed. Sun et al. demonstrates a progressive-scan segmentation method that could find the feature patterns which conform to corresponding relationship of scales through scanning the whole object [7-9]. The main weakness of this method is that it is sensitive to noises and the segmentation accuracy is low. Muniz et al. makes use of the Hough transformation to complete the image segmentation. However, this global-based method takes too much computation and the accuracy is not high [10,11]. Bai et al. uses the texture of 2-D barcode and a group of Gabor filters to acquire images' Gabor features, and the result is used to complete discrete Fourier transformation. At last self-organizing map is employed to fuse the images. This method can get a good segmentation result, but it takes too much computation. Parikh et al. divides image into four equal areas, then segments the image based on gray balance [12]. This method is more suitable for 2-D barcodes with simple background. When dealing with images with complex background this method seems unpractical. Xie et al. takes use of opening and closing operation in MM (Mathematical morphology) to filter and detect barcode image [13]. Liu et al. takes use of MM to segment gradient transformed images [14]. This kind of method is proven to be effective most of the time, but it needs different SEs choices according to different 2-D barcodes, so it is not suitable for auto image recognition.

MM is a well-known technique used in medical imaging, material sciences and computer vision [15-18]. The essence of MM processing is to take use of SE with certain scales and shapes to detect image and extract features relative to SE. The shape and the size of the SE play important role in detecting or extracting features。 As we cannot acquire any pre-knowledge about image under processing in unsupervised image processing domain[19,20], choosing suitable SE (structure element) becomes a problem. In recent years, researchers have tried various ways to solve this problem. Jalba et al. proposed a multi-scale method for object recognition based on contour information [21]. Jackway et al. proposed

doi:10.4304/jcp.8.10.2461-2468

a scaled morphological dilation-erosion operation for the scale-space smoothing of signals which can be represented as bounded real functions on R^n [22]. Mukhopadhyay et al. proposed a method of segmenting gray level images using multi-scale morphology [23], this method has a good segmentation image but the CPU time and memory space requirement are very high.

In this paper we have proposed two novel methods for segmenting gray-level 2-D barcodes on complex background using multi-scale MM reconstruction. Also, some operators to segment image are introduced. The first method uses multi-scale opening reconstruction. This method can accurately segment 2-D barcode image, but it takes a lot of time on computation thereby unable to do real time image processing. Whereas the second method improves and optimizes the first method, and reduces the computation cost while keeping a good processing result.

The remainder of this paper is organized as follows. In section II, some basic concepts of the MM approach to image segmenting are reviewed. Section III describes the proposed method which segment 2-D barcode image under complex background. The experimental results and discussions are presented in section IV. Finally, conclusions are presented in Section V.

II. Multi-scale Mathematical Morphology

MM which is an extension of Murkowski's set theory was first systematically examined by Matheron and Serra in the 1960s. It is a well-known technique used in image processing and computer vision. Morphological operators were consisted of dilation, erosion, opening, closing, and other derived transformer.

It is well known that the erosion and dilation is a pair of dual operators. The result of the erosion operation to an image shows where the SE fits the objects in the image. In gray scale, eroding an image f by SE B is defined as:

$$[\varepsilon_B(f)](x) = \min_{b\in B} f(x+b) \qquad (1)$$

The result of the dilation operation to an image shows where the SE hits the objects in the image. The dilation is denoted and defined as:

$$[\delta_B(f)](x) = \max f(x+b) \qquad (2)$$

The opening operation performs erosion first, followed by dilation; while the closing operation performs dilation first, followed by erosion [24]. The idea behind opening is to dilate an eroded image in order to recover the eroded image as much as possible. In contrast, the closing is to recover the dilated image possibly.

$$\gamma_B(f) = \delta_B[\varepsilon_B(f)] \qquad (3)$$

$$\phi_B(f) = \varepsilon_B[\delta_B(f)] \qquad (4)$$

Though the SE takes care of the shape of the features while processing the image, it cannot, however, treat objects of same shape but of different size equally.

A SE along with its higher order homothetics can process the image features based on not only shape but also size. This operation is termed as multi-scale morphology [25]. Multi-scale opening and closing are defined, respectively, as (5) and (6):

$$\gamma_{nB}(f) = \delta_{nB}[\varepsilon_{nB}(f)] \qquad (5)$$

$$\phi_{nB}(f) = \varepsilon_{nB}[\delta_{nB}(f)] \qquad (6)$$

Where n is an integer representing the scale of the SE, The n-th homothetic of a SE is obtained by dilating recursively times with itself as:

$$nB = \underbrace{B \oplus B \oplus \ldots \oplus B \oplus B}_{n} \qquad (7)$$

In MM, once an image was eroded, there is no perfect reverse transformation to recover original image. Opening operation is to some certain degree recover original image using dilation. After opening operation, image edge would be blurred. Compared with MM opening operation, opening reconstruction can recover graphics which were not completely erased by erosion. Opening reconstruction is to reconstruct the dilation of eroded image, whereas dilation reconstruction is to repeatedly dilate bounded image until stable morphology transformation is obtained.

Geodesic dilation involves two images: mark image f and mask image g, $f \le g$ and the domain $D_f = D_g$, geodesic dilation of mark image f relative to mask image g can be expressed as $\delta_g^{(1)}(f)$ when the scale value is 1. Thus geodesic dilation can be defined as the point by point minimal value of the basic dilation operation $\delta^{(1)}(f)$ between mark image and mask image.

$$\delta_g^{(1)}(f) = \delta^{(1)}(f) \wedge g \qquad (8)$$

When the scale value is n, geodesic dilation of mark image f relative to mask image g can be realized by continuously performing n times geodesic dilations on f relative to g.

$$\delta_g^{(n)}(f) = \delta_g^{(1)}[\delta_g^{(n-1)}(f)] \qquad (9)$$

Dilation reconstruction can be expressed as $R_g^{\delta}(f)$, it is defined as geodesic dilation of f relative to g until stable. When $\delta_g^{(i)}(f) = \delta_g^{(i+1)}(f)$:

$$R_g^{\delta}(f) = \delta_g^{(i)}(f) \qquad (10)$$

In (10), i represents cycle number.

When scale is n, opening reconstruction filtering are defined as [26]:

$$\gamma_R^{(n)}(f) = R_f^{\delta}[\varepsilon^{(n)}(f)] \qquad (11)$$

Because every geodesic dilation result under each scale should get minimal value with mask image, however, for condition dilation, we only need to use dilation result of

mark image under n scale to get minimal value with mask image. Thus condition dilation can reduce computation while keeping a relative good accuracy. Condition dilation $\tilde{\delta}_g^{(n)}(f)$ can be expressed as:

$$\tilde{\delta}_g^{(n)}(f) = \delta^{(n)}(f) \wedge g \qquad (12)$$

III. Proposal of Our Algorithm

In this section, we first present the theoretical background of the proposed method and then propose two algorithms in details, and compare the two algorithms' performance.

A Basics about the Algorithms

A 2-D barcode image f is a mapping from a finite rectangular subset D of the discrete plane z^2 into a limited integer N_0 .

$$f : D_f \subset Z^2 \to \{0,1,...,t_{\max}\} \qquad (13)$$

A digital grid non-directed graph ξ is the combination of vertex v and lines between vertex: neighborhood $N_\xi(v)$ of vertex v in graph ξ :

$$N_\xi(v) = \{v' \in V \,|\, (v, v') \in E\} \cdots\cdots\cdots\cdots (14)$$

Foreground $N_\xi^{\geq}(v)$ of vertex v in graph ξ is the set of neighborhood gray values of vertex v which are equal or greater than neighborhood points of v

$$N_\xi^{\geq}(v) = \{v' \in N_\xi(v) \,|\, f(v') \geq f(v)\} \cdots\cdots (15)$$

If every route in the subregion Π_i of graph ξ can be connected using points in Π_i , we can say that Π_i is connected. Based on the relationship between neighbor points, digital graph can be divided as connected and not connected.

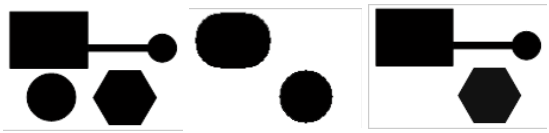
In gray image processing, image could be segmented into a series of image combinations based on specific gray values and the difference between connected subset areas:

$$f = \Pi_1 \cup \Pi_2 \cup ... \cup \Pi_n \qquad (16)$$

There are mainly two ways to recover eroded image in mathematical morphology: the first method recover eroded image using $\gamma_B(f)$. This method can only recover part of eroded image:

$$\Pi_B \geq \gamma_B(f) \qquad (17)$$

The second way is to use opening reconstruction. That is to erode original image first, then to reconstruct the image using geodesic dilation. As is shown in fig.1, compared with morphology opening operation, opening reconstruction can maintain patterns which were not removed by erosion.



1-a 1-b 1-c

Fig. 1 original image and images processed by opening operation and opening reconstruction respectively

According to set theory, the image is consisted of a number of maximally connected subsets. Where n is an integer representing the largest scale of objects or features present in the image.

$$f = \gamma_R^{(0)}(f) \cup \gamma_R^{(1)}(f) \cup ... \cup \gamma_R^{(n)}(f) \qquad (18)$$

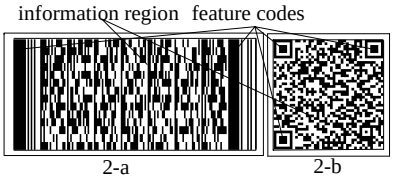
$$\gamma_R^{(n)}(f) \subseteq \gamma_R^{(n-1)}(f) ... \gamma_R^{(1)}(f) \subseteq \gamma_R^{(0)}(f) \qquad (19)$$

When the difference between two adjacent connected region areas (h, q) is m :

$$\begin{cases} q - h = m \\ \gamma_R^{(q)}(f) \subseteq \gamma_R^{(q-1)}(f) = \gamma_R^{(q-2)}(f) = ... = \gamma_R^{(q-m)}(f) \end{cases} \qquad (20)$$

B Features of 2-D Barcode

There are various kinds of 2-D barcodes today. The 2-D barcode image consists of both the bright and dark features at varying scales. According to different shapes of image, 2-D barcodes can be classified as stack code and matrix code. Most commonly used stack code includes PDF417, code49; most commonly used matrix code includes QR, DataMatrix. In fig.2 2-a is a PDF417 barcode; 2-b is a QR barcode



2-a 2-b

Fig.2 PDF417 barcode and QR code

As is shown in fig. 2, barcode image mainly consists of feature codes and information region. In some high versions, barcode images might have calibration and position information. Feature code is mainly used to identify different kinds of 2-D barcode, and feature code takes the largest connected region in the barcode image; information region consists of blanks and spaces, which represents information included in the 2-D barcode. In order to facilitate image identification, every barcode specifications specify that there should be a circle of white blank outside barcode information region. This blank region is to separate barcode image from background and it has much bigger connected region than feature region.

C Implementation:

Images acquired by camera often degenerate by noises and uneven lighting. In order to prevent these bad factors from disturbing our image segmentation, we divide algorithm into preprocessing algorithm and segmentation algorithm.

C.1 Preprocessing algorithm

Image preprocessing includes image filtering and illumination normalization. Berlemeont et al. mentioned several self-adaptive image filtering algorithms [26-28], in this paper we take use of algorithm in Li et al. to do the filtering process [29], and then we use multi-SEs morphology to realize illumination normalization. Here is the main process of illumination normalization:

1.1) Choosing four linear SEs with angles 0°, 45°, 90°, 135° respectively, and the scale of SEs should be $1/4$ of the smallest scale of image line and column.

1.2) Using big-scale SEs in step (1.1) to perform white Top-hat transformation on original image, we can obtain each SE's corresponding images S_i .

1.3) Using the information entropies as weights and taking images acquired in step (1.2) to do weighted summation we can obtain filtered and illumination normalized image.

C.2 segmentation algorithm 1

Erosion can erase image features which is smaller than SE. However, opening reconstruction can keep features which were not completely eroded in image, so these parts can be recovered in opening reconstruction. This means that every object which cannot contain SE will be erased while others will keep the same. Every time performing erosion and an opening reconstruction is just like sieving with a net, all objects which are smaller than the hole of net will be filtered and others will remain. According to the relationship between each connected regions in 2-D barcode image, proposed segmentation algorithm can be described as is shown in fig. 3.

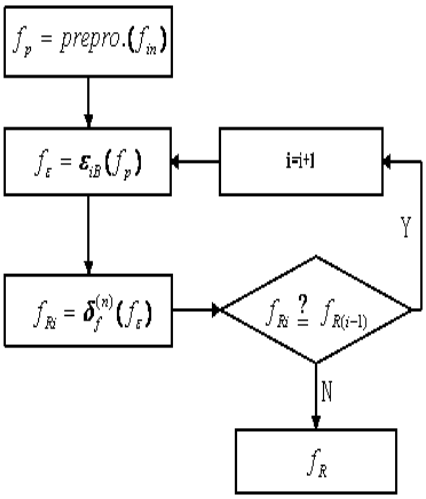


Fig. 3 Flow of multi-scale opening reconstruction algorithm

2.1) Using disc SE iB to erode original image f we can get eroded gray image f_i:

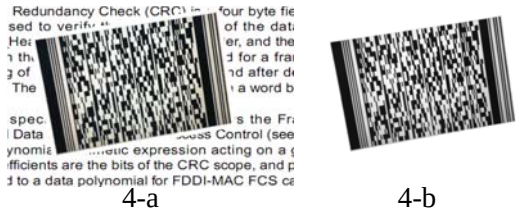
$$f_i = [\varepsilon_{iB}(f)](x) \qquad (21)$$

In equation (21) B is a base SE with scale of 1.

2.2) Take eroded image f_i as mark image and original image f as mask image to do geodesic dilation reconstruction:

$$R_f^\delta = \delta_f^{(n)}(f_i) \qquad (22)$$

2.3) Comparing the opening dilation reconstruction result with the last reconstruction result, if they were not the same, we select the next higher homothetic of the SE and go back to step (1); if they were the same, algorithm will be terminated and final image is acquired. Fig. 4-a is the input image. Figure 4-b is the segmented image.



4-a 4-b

Figure 4 original image and segmented image

The process above is what we called multi-scale opening reconstruction based segmentation algorithm for 2-D barcode. This algorithm can perfectly segment 2-D barcode region out of the background. Assuming that the maximal scale of multi-scale opening reconstruction is m, when the scale is i the corresponding geodesic dilation scale is $n(i)$, thus the whole times geodesic dilation need to perform $\sum_{i=1}^{m} n(i)$. For an image with $M \times N$ resolution, the computation time complexity is $O(NM\sum_{i=1}^{m} n(i))$. We simulate this algorithm using MATLAB 7.0 on PC and it costs 30minutes to achieve the final results. The PC configuration includes Intel Core 2 Duo T6600 CPU and 2GB RAM and 32bits windows 7 operation system. This is too much for real time image processing.

C.3 The second proposed algorithm

In real-time 2-D barcode identification, the number of barcodes which can be identified per second is mainly decided by the image processing time. According to the analysis above, algorithm in C.2 cost too much time on computation. This algorithm improves the disadvantage of the first one. This algorithm can be divided into rough extraction and fine extraction, preprocessed image is taken as the input. The flow of algorithm is shown in figure 5:

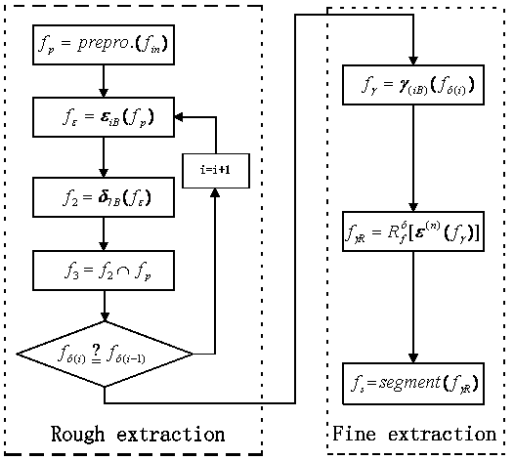


Figure 5 Flow of multi-scale condition reconstruction algorithm

3.1) Using disc SE B to erode image and get eroded gray image:

$$f_\varepsilon = \varepsilon_{iB}(f_p) \tag{23}$$

In order to further reduce timing cost, we perform a simple binaryzation in rough extraction process. That means we firstly implement binaryzation on eroded image, and then perform condition dilation. We take $1/2$ of the sum of maxim and minimal gray value as the threshold, all pixels which are bigger than threshold will be set to 255 and pixels which are less than threshold will be set to 0.

If skipping binaryzation and performing gray computation, the time complexity of each pixel would be $O(n^2)$ using typical bubbling method. Even using fast sorting algorithm the time complexity would also be as large as $O(n\log_2 n)$, and the result is unstable. Implementing binaryzation first would cut time complexity down to $O(n)$, thus reducing timing cost.

This simple binaryzation would make image details fuzzy, however, at this step we just roughly mark the region 2-D barcode located and don't implement fine extraction, so this binaryzation will not affect the final result. At the same time, comparing with gray image, binaryzation can increase contrast of image and facilitate image extraction.

3.2）Expanding the scale of disc SE and implementing dilation on eroded image.

As opening is non-expand operation, when $i \le j$, $f \circ iB \ge f \circ jB$, that means as the increase of the scale of SE image tends to shrink. If $n \to \infty$, then $f \circ nB \to 0$. In practical application, value of n is decided by the biggest connected region in image. As long as the SE scale under value n is bigger than the value of the biggest connected region in image, erosion in opening operation would erode image to an empty set. To avoid image shrink in opening operation, scale of SE should be bigger than erosion scale in condition dilation so that noise could be erased while regions where original image located remain as much as possible. When the scale of dilation SE is one pixel larger than the scale of erosion SE, flat region in object area would not shrink, but the computation is still intensive and could not make sure that regions with sudden change would be recovered. From fig. 2 we can see that blank circle outside barcode graph has the largest connected region compared with other parts in the barcode image. Thus the best dilation SE should be much bigger than erosion SE. That is to improve speed by sacrificing accuracy. Certainly dilation SE should not be too big because the dilation result might take over the whole image and all image regions would be marked out. Through experimenting on various 2-D barcode like QR, PDF417 we get that the scale of dilation SE should be less than 10 times of the scale of erosion SE, in this paper, we choose 7 times.

$$f_2 = \delta_{7B}(f_\varepsilon) \tag{24}$$

3.3) Taking original image as mask and limiting dilated image under original image, in this way we can roughly mark out the region of 2-D barcode.

$$f_3 = f_2 \cap f_p \tag{25}$$

In this paper we term (3.2)-(3.3) as multi-scale condition reconstruction algorithm. If the maxim scale of multi-scale opening reconstruction loop is m, then condition dilation need to process only once. For an image with $N \times N$ resolution, computation time complexity is much less than the first algorithm.

$$O(mN^2) \ll O(N^2 \sum_{i=1}^{m} n(i)) \tag{26}$$

3.4）Comparing rough extraction result with the last extraction result, if they were not the same, then select the SE $(n+1)B \to B$ and jump to step (3.1), otherwise terminate the rough extraction algorithm.

C.4 Fine extraction of barcode region

After rough extraction of barcode region, noises may still exist at edge of the barcode image. Using typical opening operation can erase those noises but it is hard to decide the scale of SE. Multi-scale method could be used to deal with different scales and different kinds of image, but it takes a lot of time. Multi-scale opening reconstruction in rough extraction already provides us with the SE iB with which image get stable. We can appropriately expand the scale of iB then use it to do an opening operation.

$$f_n = \gamma_{iB}(f_i) \tag{27}$$

By now, object has already been extracted. Because we choose disc SE in typical opening operation and it will rounding the vertex, so we still need to do some job to realize fine extraction. Taking image f_n as mark image and preprocessed image f_p as mask image, we perform geodesic dilation until stable. As image f_n slightly smaller than 2-D

barcode object, image would be quick to stable. Finally we obtain the final extraction 2-D barcode result. We simulate the second proposed algorithm under the same environment as the first algorithm, and it costs only 10 seconds to achieve the final results. This indicates that the second algorithm is much faster than the first algorithm which costs 30 minutes to finish a simulation.

IV. Algorithm Verification

According to different kinds of 2-D barcode, this paper employs the most popular PDF417, QR code to evaluate the proposed approach. Experiments mainly focus on verifying proposed approach's adaptive capacity on different barcode's scales, tile angles and textures.

A Verifying Proposed Approach's Adaptive Capacity on Different Barcodes' Scales

In MM, SE plays a key role. The processing result would be degenerated with the decrease of match degree between SE and concerned features. In order to obtain a good processing result, SE is usually chosen according to the priority knowledge of concerned features' scale in image. In auto-identification analysis, one cannot know the scale of concerned features in advance, so finding a scale-adaptive morphological algorithm is of great significance. Relative scales include the size of concerned features and the proportion of concerned features accounting the whole image. In fig. (6-a) and (6-d), barcode images possessed $2/3$ and $1/10$ of the whole image respectively. Fig. (6-b) and Fig. (6-e) are the processing result of fig. (6-a) and (6-d) using our algorithm. Fig. (6-e) and fig. (6-f) are images which were extracted from original images with corresponding coordinates of segmented images.

From the experimental results the Fig. (6-b), (6-e), (6-c), (6-f), we can see that our algorithm can adaptively process images with different resolutions and different proportions of 2-D barcodes as well. It indicates that proposed algorithm has a good adaptive capacity on different barcode's scales.

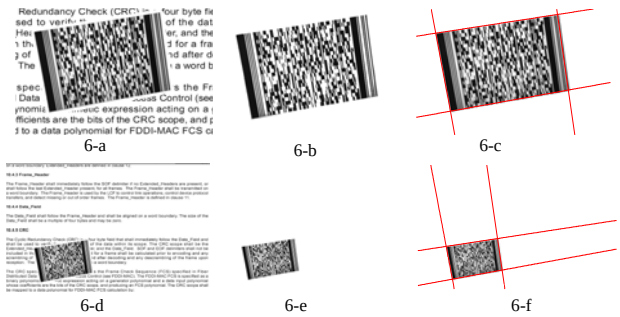


Fig.6 Segmentation results of barcode images with different scales

B.Verifying Proposed Approach's Adaptive Capacity on Different Barcode's Tile Angles.

There are two kinds of 2-D barcode identification devices: fixed and handheld. Fixed 2-D barcode identification device placed in fixed terminal; handheld device include 2-D barcode scanner gun and portable PDA device. When users capture image with a PDA which has a camera, it is difficult for them to hold devices at a perfectly right angel.

In mathematical morphology, SEs in different directions can get image's information on corresponding directions. As a result, image's information can be kept complete even though image has been inclined.

Fig. (7-a) and (7-d) are images with different tile angles. Fig. (7-b) and (7-e) are images processed by proposed algorithm. Fig. (7-c) and (7-f) are images which were extracted from original images with corresponding coordinates of segmented images. From the experimental results we can see that proposed algorithm can adaptively process different tile angles. This indicates that proposed algorithm has a good adaptive capacity on different barcode's tile angles.

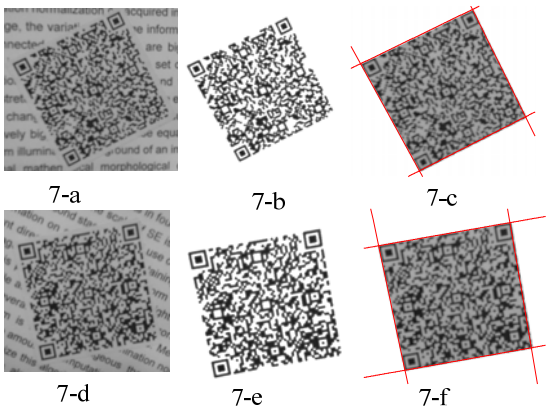


Fig.7 Segmentation results of barcode images with different tilt angles.

C. Verifying Proposed Approach's Adaptive Capacity on Different Types of 2-D Barcodes.

According to shape, 2-D barcodes can be classified into stacked code and matrix code. Stacked 2-D barcode is stacked by certain kind of 1-D barcode, and different kinds of 1-D barcode can form different kinds of 2-D barcode; matrix 2-D barcode consists of matrix. Different types of 2-D barcodes own different textures. In MM, processing image needs to choose different SEs according to different textures. Textures in 2-D barcode include image signature, size of connected areas of data code and difference between shapes and scales.

Fig. (8-a) is PDF417 2-D barcode image, fig. (8-d) is matrix QR barcode image. Fig. (8-b) and fig. (8-e) are the processing results of original images, Fig. (8-c) and fig. (8-f) are images which were extracted from original images with corresponding coordinates of segmented images.

From the results, we can see that proposed algorithm can adaptively process different kinds of 2-D barcodes. This indicates that proposed algorithm has a good adaptive capacity on different kinds of 2-D barcodes.

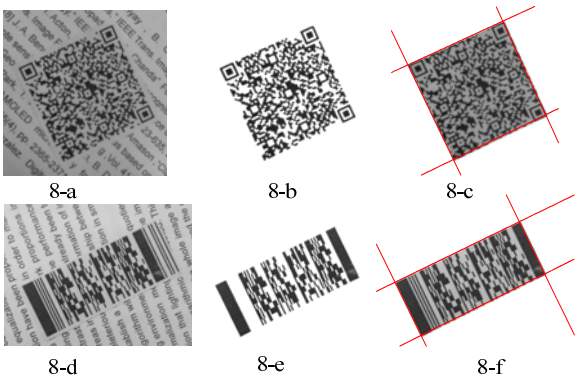


Fig.8 Segmentation results of different kinds of barcode images.

V. CONCLUSION

In this paper, two methodologies for a robust and efficient segmentation of 2D barcode images of different shape and size is presented. The methodology builds on existing work, but extends it to achieve efficiency and robustness. The first method is a classic application of multi-scale opening reconstruction. This method has a good segmentation result but costs intensive computation. To solve this problem, we propose the second segmentation method. This method consists of three parts. Firstly, it preprocesses image to filter noises and normalize illumination. Secondly, it roughly marks out the located region of barcode image. In this part it uses binaryzation and condition dilation to greatly reduce the computation cost. Thirdly, it implements opening operation and geodesic dilation on the region obtained in the second part to get precise region of 2-D barcode. The presented techniques have been evaluated by using these techniques to process several 2-D barcode images. Results show that this method has a good adaptability and can automatically and accurately segment different kinds of 2-D barcode with different scales and tilt angles under complex background. By now, our algorithm still needs processor to possess a relative large storage space and time, the next research will mainly focus on optimizing and reducing storage space and implement this algorithm using VLSI architecture thereby designing a hard IP of 2-D barcode segmentation.

REFERENCE:

[1] R. C. Palmer," The bar-code book," Helmers Publishing, Peterborough, 1989.

[2] S.K. Kuo, S.L. Chen, C.T. Lin,"Design and development of RFID label for steel coil," IEEE Trans. Industrial Electronics, Vol.57 (6), pp.2180-2186, June 2010.

[3] H. Kato, K.T. Tan, "Pervasive 2D barcodes for camera phone applications," IEEE Trans. Pervasive Computing, Vol.6 (4), pp.76-85, 2007.

[4] Z.Y. Ma, Y. Hong, M.H. Zhang, M. Su,"Encoding and decoding nanoscale thermal barcodes for ultrahigh capacity identification systems,"IEEE Trans. Applied physics letters, Vol.95 (23), pp.101-103, 2009.

[5] S.W. Pei, G.B. Li, B.F. Wu, "Codec system design for continuous color barcode symbols," in Proc. IEEE Int. Conf. Computer and Information technology workshops, pp.539-544, 2008.

[6] L. L. Hu, Y.H. Wang, D. Li, J. Li, "A hybrid client/server and browser/server mode-based universal mobile ticketing system," in Proc. IEEE Int. Conf. on Information Management and Engineering(ICIME),2010,pp. 691-695.

[7] M. Sun, Zh. K. Fang,Sh. H. Zhang, "Research of automatic recognition algorithm of Chinese sensible code, " in Proc. IEEE Int. Conf. on Global Congress on Intelligent Systems(GCIS), pp.492-499,2009.

[8] J. H. Li, P. Li ,X. D. Li ,Y. W. Wang ,"A skew detection algorithm for PDF417 based on feature point," IEEE Trans. Measuring technology and mechatronics automatic ,Vol.4(1),495-499,2012.

[9] H. I. Hahn, J. K. Joung,"implementation of algorithm to decode two-Dimensional barcode PDF-417,"in Proc. IEEE Int. Conf. on Signal Processing, pp.1791-1794, 2002.

[10] R. Muniz, L. Junco, A. Otero," A robust software barcode reader using the Hough transform," in Proc. IEEE Int. Conf. on Information Intelligence and Systems, pp. 313-319,1999.

[11] Zh. F. Bai, Zh. X. Yang, J. P. Wu, Y. Cheng, "Region localization based on rotational invariant feature and improved self organized map", in Proc. IEEE Int. Conf. on intelligent system and knowledge engineering, pp. 703-706, 2008.

[12] D. Parikh, G. Jancke,"Localization and segmentation of a 2d high capacity color barcode," in Proc. IEEE Int. Conf. on Applications of computer vision, pp. 1-6, 2008.

[13] J. X. Xie, Zh. H. Tang, W. H. Gui, H. Gong,"Edge detection algorithm in two-dimension bar code based on mathematical morphology," ASPT. Computer engineering and applications, Vol.24, pp. 197-199, 2008.

[14] F. Y. Liu, J. P. Yin, K. Li, Y. Li,"Research on the location of PDF417 under the complicated background," ASPT. Computer engineering &science,Vol.32(6),pp.55-57,2010.

[15] R. J. O'Callaghan, D. R. Bull,"Combined morphological-spectral unsupervised image segmentation," IEEE Tran. , Image processing, Vol. 14(1), pp. 49-62, 2005.

[16] M. E. Plissiti ,C. Nikou, A. Charchanti ,"Automated detection of cell nuclei in pap smear images using morphological reconstruction and clustering,"IEEE Trans.,Information technology in biomedicine, Vol.15(2), pp.233-241, 2011.

[17] M. Droske, M. Rumpf, "Multiscale joint segmentation and registration of image morphology," IEEE Trans. Pattern analysis and machine intelligence, Vol.29 (12), pp. 2181-2194,2007.

[18] J. Zhi, J. Y.Liu, H.Yuan,et al. "Design of Simulated Pattern Painting Based on Image Segmentation and Recognition Method" Journal of Software, 2011,Vol. 6(11), 2232-2238.

[19] Z. l.Ji, D. M. Meere, I.G.chev,et al. "Implementation and Deployment of an Intelligent Framework for Utilization within an InfoStation Environment",Journal of Software, vol. 7(5) , 935-942.

[20] L.B.Li,"Efficient Fast Object-Tracking Scheme Based on Motion-vector-located Pattern Match",Journal of Software,vol.7(5) 998-1005.

[21] A. C. Jalba, M. H. F. Wilkinson, J. B. T. M. Roerdink, "Shape representation and recognition through morphological curvature scale spaces," IEEE Trans. Image processing, VOL.15(2), pp.331-341,2006.

[22] P. T. Jackway, M. Deriche,"Scale-space properties of the multiscale morphological dilation-erosion," IEEE Trans. Pattern Analysis and Machine Intelligence, VOL. 18(1), pp. 38-51, 1996.

[23] S. Mukhopadhyay, B. Chanda,"Multiscale morphological segmentation of gray-scale images," IEEE Trans. Image processing, vol. 12(5), pp. 533-549, 2003.
[24] L. Vincent," Morphological grayscale reconstruction in image analysis: applications and efficient algorithms," IEEE Trans. Image Processing, VOL.2 (2), pp.176-201, 1993.
[25] J. I. Pastore,E. Moler, V. Ballarin,"Multiscale morphological operators and geodesic distance applied to computed axial tomography segmentation," IEEE Latin America transactions, VOL.5(1), pp.28-31,2007.
[26] C. F. N. Cowan, J. Mavor,"Design and performance evaluation of a 256-point adaptive filter," IEE Proc. F, Communications, Radar and signal processing,VOL.127(3), PP.179-184,1980.
[27] Sh. Zh. Du, B. J. Van wyk,Ch. L. Tu,X. H. Zhang,"An improved Hough transform neighborhood map for straight line segments," IEEE Trans. Image processing,VOL.19(3), pp.573-585,2010.
[28] S. Berlemont, J. C. Olivo-Marin,"Combining local filtering and multiscale analysis for edge ridge and curvilinear objects detection," IEEE Trans. Image Processing, VOL.19 (1), pp.74-84, 2010.
[29] T. Law, H. Itoh, H. Seki,"Image filtering, edge detection and edge tracing using fuzzy reasoning," IEEE Trans.Pattern Analysis and Machine Intelligence,VOL.18(5), pp.481-491,1996.

Jianhua Li received the M.A. degree from wuhan institute of physics and mathematics, Chinese academy of sciences. He is currently pursuing the PH.D degree in school of micro-electronics and solid-state electronics, university of electronic science and technology of china. His current interests are image procession and pattern recognition.

Yiwen Wang received his B.S. degree and Ph. D. degree in electrical engineering from Wuhan University and Tokyo Institute of Technology, respectively. From 1988 to 2000, he worked as a senior VLSI design engineer in Northeast Micro-electronics Institute of China. From 2005 to 2007, he worked as a special associate professor in Tokyo Institute of Technology. He is currently a professor in University of Electronics Sciences and Technology of China. His research interests include reconfigurable SoC architecture, Fingerprint authentication, and Machine vision. Etc.

Ping Li was born in Sichuan Province, China, in1957.He received the B.S. and the M.S. degrees from UESTC in 1982 and 1987, respectively, both in microelectronic engineering. He is now full Professor and Deputy Director of State key Laboratory of Electronic Thin Films and Integrated Devices UESTC. His research interests include FPGA design and test, SOC design and verificatio