Identification of QR Codes Based on Pattern Recognition

Ming SUN, Zhenkun FANG, Longsheng FU, Fan Zhao
College of Information and Electrical Engineering, China Agricultural University
Beijing 100083, China
drmingsun@163.com

Abstract

To avoid the limitation of present QR code algorithms which are only available on the paper presswork, this paper proposed an algorithm based on Pattern Recognition to realize the identification of the QR codes printed on various materials with different models. The QR codes from the sample images were manually marked first, and then the input images were divided into blocks. For every single block, its MRH and LBP features were calculated and such texture patterns were trained to obtain a QR code identifier using the Spatial Boost algorithm. For real-time identification, this identifier could divide the real-time input images, and output the classified results of the blocks, considering the texture features (MRH, LBP) of the blocks as input vectors. The blocks confirmed to be 2D barcode were combined into QR codes. The QR codes identifier obtained by the last training reached a 100% rate of detection in the test database of the experiment.

Key words：QR Code; Pattern Recognition; Multi-Resolution Histogram; Local Binary Patterns; Spatial Boost

1. Introduction

Barcodes, which are considered as an automatic recognition method with high-speed reading, high-accuracy, low-cost and high-reliability, is widely applied in commodity labels, data security, anti-counterfeiting, electronic commerce and many other fields [1-2]. Comparing with a one-dimensional barcodes, a two-dimensional (2D) barcodes carry information along both horizontal and vertical directions, enabling greater information capacity, higher reliability and supporting different levels of error correction. So far, the common 2D barcodes are PDF417 code, Data Matrix code and QR code. Among all these codes, Quick Response (QR) code is a typical matrix two-dimensional barcode as illustrated in Figure 3. It has many advanced features, such as readability from any direction and high efficiency in storing Chinese characters. The application of 2D barcodes combines the technology of automatic recognition, encoding, decoding and printing of barcodes together, among which the automatic recognition of barcodes is the most important subject[2]. To generalize the application of 2D barcodes in commodity labels, automatic recognition technology of their images confronts some difficulties as follows:

(1) Since the barcodes are printed on the wrapping of the commodities, the background in a barcode image often contains irrelevant information (noises), such as the characters, symbols and patterns on the wrapping. These noises will differ because of the variety of commodities which brings additional difficulties to the task of locating the barcode in the image.

(2) There will be geometric distortions, such as deflection distortion, perspective distortion and scale distortion etc [3], in the barcode image due to multiple reasons: the angle diversity between the optical axis of the image collecting equipment (such as the barcode reader) and the barcode plane, the rotation angle diversity between the optical axis and the barcode plane, the distance diversity between the collecting equipment and the barcode plane, the lack of flatness of the barcode plane etc. All these distortions can make the reading of the barcode module, especially the high-density barcode (like QR code whose module scale is less than 0.20mm×0.20mm), a very tough job.

(3) For high-density barcodes, since the effect of PSF (point spread function) in image acquisition device, blurring and overlapping often appear on the boundary. It is not suitable to use the first order differential method [4-5] which is commonly applied to find the boundary of barcode images.

1.1. The conventional identification algorithms of QR codes

In view of the above issue, many experts and scholars have done considerable research and developed many identification algorithms which are the same as the reference decoding algorithm of QR code international standards[6].

This paper focused on the segmentation and location of QR code images. The images collected by image acquisition devices are always either colorful or gray-scale images, but the original QR codes are black/white images, so we need to convert the acquired barcode images into black/white images. Generally, the thresholding method was used to convert them; the most important step of this method was the selection of the threshold value. The reference algorithm of QR code international standard[6] calculated the average value of the biggest and smallest gray value of the barcode image, but it would be impacted by noise easily, and its stability was very low. Liu Dong et al.[7] took the histogram with double peak method to get the threshold. This method could obtain the desired effect in most cases, but when the light around the barcode was relatively weak or strong, the two peaks are not obvious, and the method would fail. Hu Xiaopeng et al.[8] used the OTSU's to get the threshold, but the computation of this method was so large that the efficiency can be reduced when image quality was good. Liu Yue et al.[9] developed the adaptive-thresholding method by analyzing the peak of the image histogram, according to various situations, adopted difference thresholding methods, and improved the efficiency.

There were three identical Finder Patterns located at the upper left, upper right and lower left corners of the symbol respectively as illustrated in figure 2. Each finder pattern might be viewed as three superimposed concentric squares and was constructed of dark 7×7 modules, light 5×5 modules and dark 3×3 modules. The ratio of module widths in each finder pattern was as illustrated in figure 2. The symbol was preferentially encoded so that similar patterns had a low probability of being encountered elsewhere in the symbol, enabling rapid identification of a possible QR Code symbol in the field of view. Identification of the three finder patterns comprising the Finder Pattern then unambiguously defined the location and rotational orientation of the symbol in the field of view.

1.2. Identification of 2D barcodes based on pattern recognition

However, the identification algorithms mentioned above were only available to recognize the QR codes which are on the surface of paper presswork and could not decode the one on plastic or metallic materials as illustrated in figure 3. In these situations it was hard to use the finder pattern to locate the QR code, because the Finder Pattern could not implement the proportion (dark: light: dark: light: dark =).

In practical application, 2D barcodes were widely adopted on the surface of different materials. The texture features of different material were dissimilar, and the models of the QR code's modules were unlike each other, there were dots, seriate squares and discrete squares. Due to different materials and application situations, the generations of the QR Code are also differed. Usually, we adopted barcodes printer or print directly onto the paper presswork and labels, Laser Printing on the plastic surface, Dot Printing, Laser Carving or Electro-Chemical Etching on the metal surface[10].

This paper provided a method based on pattern recognition to decode the QR codes of different modules on various materials, and the algorithm included two sections which were training and real-time identifications. In training section, we would first mark the QR codes in sample images and split the input images into different blocks manually. In each sub-block the method calculated the image texture features such as MRH (Multi Resolution Histogram), LBP (Local Binary Pattern) which were invariant to the gray-scale and rotation, and then trained the texture features through the Spatial Boost algorithms established by Shai Avidan to get a QR code identifier. In the real-time identification section, the identifier would split the input image and use the texture characters as the input vector to output the classified results, which was to classify the sub-image into background or 2D barcode, and then combined the sub-blocks which were 2D barcode into QR code.

2. Pattern Recognition

Pattern Recognition is the process to describe, recognize, classify and interpret the things and phenomenon by managing and analyzing various forms of information which are taken from things or phenomenon. The number of the categories is determined by the particular recognition issue. In this paper all the things are divided into two classes: object (QR codes) and background.

2.1. Pre-processing

The pre-processing of QR code images exerted an essential effect in the whole identification system which directly influenced the accuracy of identification. During the shooting process, it was inevitable that the QR code images might be distorted, leaned or unevenly exposed. The pre-processing mainly aimed to eliminate the factors which would bring the serious negative influence and to enhance the rate of identification. In this algorithm, the pre-processing included two sections: gray processing and filtering.

2.1.1. Gray processing. The original QR code image was composed of dark and light modules; however, in usual cases the collected images were colorful. The colorful images contained massive information so that the cost of storage was colossal and the executive speed of the system was greatly reduced. Because that each pixel of the image contained three components of colors, it meant that there were lots of irreverent information that would bother the advanced identification. So we always converted the colorful image into a gray-scale image during the identification process to accelerate the recognition speed. The weighted average method was used as illustrated in formula 1[11]:

$$I = 0.30R + 0.59G + 0.11B \qquad (1)$$

2.1.2. Image filtering. The collected QR code image contained certain noises, and the source was the illumination collecting system whose noise was mainly composed of Salt & Pepper noises which accorded with the Poisson distribution. The noise would be effectively reduced by the Spatial Adaptive filter[12]. Spatial Adaptive filter could be divided into two kinds according to the mathematic form: the linear filters and the nonlinear ones. The median filter of nonlinear filters could preserve the marginal acutance and the details of the image during the filter process. As a result, we chose the median filter to reduce the noises[13].

2.2. Feature selection and extraction

To identify the QR code by the method of pattern recognition, we needed to collect the characters from the image to describe the QR code. This paper described the QR codes with the texture features. In practical application, there would be geometric distortion, such as deflection distortion, perspective distortion and scale distortion etc, in the barcode image due to multiple reasons: the angle diversity between the optical axis of image collecting equipment (such as barcode reader) and the barcode plane, the rotation angle diversity between the optical axis and the barcode plane, the distance diversity between the collecting equipment and the barcode plane, the absence of flatness in the barcode plane and various other factors. So the texture features chosen should be invariant to gray-scale and rotation, as this paper adopted multi-resolution histogram and local binary patterns.

2.2.1. Multi-Resolution Histogram. Efstathios et al.[14] established a method to collect the texture features based on the Multi-Resolution Histogram (MRH). MRH features had the advantages of less calculation, robustness to noises, high efficiency and invariant to the gray-scale and rotation. MRH was used for image matching because it is sensitive to image structure. In addition, multi-resolution collected the space information of image textures.

Generally, images were divided into sub-blocks; we needed to calculate the MRH feature of each sub-block. First, we tried to obtain the multi-resolution images $R_1, R_2, \cdots, R_{i-1}$ of sub-block image R_0 . To each sub-block image we calculated the gray-scale histogram $L_0, L_1, \cdots, L_{i-1}$ and then combined the differences of adjacent histograms into a vector which was the MRH feature vector as illustrated in formula (2).

$$H = [L_1 - L_0, \cdots, L_{i-1} - L_{i-2}] \qquad (2)$$

Generally, the gray-scale of images ranged from 0 to 255 after graying, totalling up to 256 grades; however, the resultant MHR feature vector is impractically large.[0] The similarity of most images was mainly determined by some thick textures. According to a human's visual character, it was impossible for a person to differentiate excessively thin texture and it added the calculation. Therefore, we compressed the gray-scale of the original image in order to cut down the calculation, such as compressing to 64 grades, 32 grades or 16 grades. It was discovered in the experiment that the three gray grades have similar effects; moreover, when it was on the 16 grades, the speed of feature collecting was more than doubled. According to this, we could compress the original image to 16 grades, which was from 0 to 15 grades. In this paper, we used four kinds of resolving capability (including the original image), and every gray histogram was a 16 dimensional vector, so that the MHR feature of every block was a 48 dimensions vector.

2.2.2. Local Binary Patterns. In recent years, a series of new analysis method of texture characters, represented by LBP algorithm which analyze the stable window characters[15] and used the statistical method to collect the whole characters, appeared. LBP algorithms are usually defined as windows sized 3×3 or 5×5 and pixels of an image block labeled by thresholding the neighbourhood of each pixel with the center value. Then, we got the LBP value by weighting sum according to different positions of pixels. The LBP character was also invariant to the gray-scale and rotation of images.

Where g_0 corresponded to the grey value of the center pixel and g_p to the grey values of the P neighbourhood pixels. The function $s(x)$ was defined as follows: $s(x)=\begin{cases}1 & x\geq 0\\ 0 & x\prec 0\end{cases}$. See Figure 4 for an illustration of the operator which worked with the 3×3-neighbourhood of a pixel.

During the process of the texture feature analysis above, the window size of the LBP method was fixed beforehand and it had nothing to do with the details of the image which led to some errors when distilling the texton's feature so that it was difficult to adapt to the requirement of different level of roughness concentration and yardstick texture. The adaptive-LBP algorithm which was developed by Mao Bingyi[16] solved the issue effectively. The algorithm first designed Tamura roughness concentration algorithm which lived up to the LBP requirement, and then got the approximate size of the texture textons and combined the size with the LBP algorithm to reach the purpose of the self-adaptive analysis window.

2.2.3. Design of classifier. Schapire established the Boosting algorithm in 1990 which could enhance a group of weak learning algorithms to strong learning algorithm. In 1997, Freund and Schapire[17] developed AdaBoost algorithm which combined the weak classifiers into a strong classifier. The basic thought was to reduce the weights when the classifier is classifying some samples correctly and increase weights when classifying some samples incorrectly, in order to concentrate on studying the difficult training samples during the procedure of studying. Eventually, a classifier with high accuracy as illustrated in the formula (4) was obtained.

$$H(x)=\sum_{t=1}^{T}\alpha_t h_t(x) \qquad (4)$$

where $h_t(x)$ is weak classifier and α_t is classifier weight.

$H(x)$ is the strong classifier from the training which is also the linear combination of several weak classifier $h_t(x)$, $h_t(x)$ is based on the texture feature, this weak classifier takes the texture feature vector of every single block as its input, but does not use the spatial information between blocks.

The nine sub-blocks as illustrated in Figure 5, the strong classifier $H(x)$ trained by AdaBoost will classify the center sub-block into background because it didn't have the features of 2D barcodes. But from the space aspect, the 7 surrounding sub-blocks had gotten certain texture characters of 2D barcodes. The sub-blocks could be classified correctly if we ascertained the result of classification based on the classification result of the surrounding sub-blocks.

The SpatiaBoost put forward by Shai Avidan[18] added a weak classifier based on spatial information during the training process of AdaBoost. It combined the weak classifier based on texture features and the weak classifier based on space as a strong classifier as illustrated in formula 5:

$$H(x)=\sum_{t=1}^{T}\alpha_t(\lambda_t h_t(x)+(1-\lambda_t)h_t'(x)) \qquad (5)$$

Where α_t is represented combination coefficient, $\lambda_t\in\{0,1\}$ is classifier weight. Weak spatial classifier $h_t'(x)$, which was composed of MRH, $LBP_{8,1}$ and $LBP_{16,2}$ of sub-blocks, calculated the feature vector of x by the classification results of neighbourhood sub-blocks.

3. Results of Experiments

To prove the capability of the algorithm, we used the image collecting device to collect 40 glass-etched images of QR code of size 640x480, of which 20 will be the sample images. We marked out the QR codes in the sample image manually and split the input image into sub-blocks. The blocks in the marking range were the positive samples while those not were the negative ones. To each sub-block, we calculated the texture features which are invariant to gray-scale and rotation: MRH and LBP. Then we used the SpatialBoost algorithm to train the texture features and obtain a QR code identifier. The negative 20 images will be the testing image and accuracy rate of the QR code identifier turned out to be 100% during the training process.

4. Conclusions

To avoid the limitation of present QR Code algorithms which are only available on the paper presswork, this paper proposed an algorithm based on pattern recognition to identify the QR Codes printed on various materials with different models, an algorithm which includes training and real-time identification. And the methods employed in this paper could overcome the probable problems of highlights, shadow and angle incline. For real-time identification, this identifier could divide the real-time input images, and output the classified results of the blocks, namely to classify the image blocks as background or QR code, considering the texture features (MRH, LBP) of the blocks as input vectors. The blocks confirmed to be 2D barcode were combined into QR Codes. The QR Codes identifier obtained by the last training reached a 100% rate of detecting in the test database of the experiment.

5. References

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