Robust Hazy QR Code Recognition based on Dehazing and Improved Adaptive Thresholding Method

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***Abstract*— Quick Response (QR) code has been extensively used in our daily life. But in some complex environments such as hazy conditions, QR code recognition is difficult. In this paper, a robust QR code recognition algorithm in complex hazy environments is proposed. First, contrast-limited adaptive histogram equalization is implemented to enhance original pictures. Then Gated Context Aggregation Network is modified to obtain dehazed QR code images. After that, an adaptive thresholding method is used to obtain binary images. Finally, binary QR code is decoded. For training and testing our algorithms, we collect a set of benchmark of hazy QR code images including hazardous chemical name, Chemical Abstracts Service number, shape and properties such as flammable, explosive, corrosive and toxic. Ablation comparison and experimental results on our own database demonstrate our proposed algorithm achieves superior performance on hazy QR code recognition tasks.**

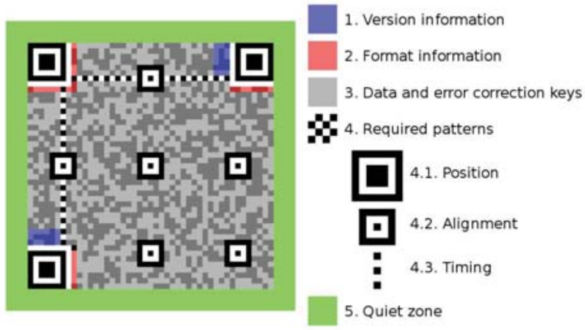

Fig. 1: Structure of QR code(version 7). It comprises Version information, Format information, Data and error correction keys, Required patterns and Quiet zone. Required patterns could contain the information of Position, Alignment, Timing, etc.

I. INTRODUCTION

QR code is the trademark for a type of 2D barcode which was first designed in 1994 for the automotive industry in Japan. As shown in Fig. 1, QR code has a standard structure including information of version, format, required patterns and so on. Nowadays it has experienced an enormous increase due to high-speed growth of mobile payment, social software and other applications. QR code is an effective data collection tool and has been exploited in many aspects including product tracking, website redirection, time tracking, document management, storage progress, etc. Because of its low cost and easy sharing, QR code is also used in some occasions with complex backgrounds which makes the recognition problems highly challenging to solve [1].

The problem of QR code recognition has been studied extensively before. Zamberletti et al. [2] present a novel approach using a supervised machine learning algorithm for 1D barcode detection. Leong et al. [3] introduce a method based on keypoint selection and line detection for 2D barcode extraction. Although these previous works have high detection rates on certain barcodes, the performance of these methods may be influenced in some complex environmental conditions such as particles and droplets of water in the atmosphere. For example, haze, fog and smoke are these circumstances. Foggy condition decreases the contrast of the affected region of QR code images and causes details lost. Because of this, the visibility of QR code in foggy weather would be dramatically degraded. The degraded QR code images may lose significant information and color fidelity, as shown in Fig. 2 (b), which makes QR code hard to be decoded.

Dehazing problems are extremely valued between digital image processing and machine learning projects. Many traditional algorithms [4]–[7] yield several image priors and visual cues to predict significant parameters in order to complete lost information during the corruption process. For example, He et al. [4] propose the dark channel prior. Depending on a large amount of statistics, He et al. find that in at least one color channel, clean outdoor images often contain some low-intensity value pixels. Pei et al. [5] first estimate weather conditions and then use these conditions to remove nighttime fog. Zhu et al. [6] propose color attenuation prior based on establishing a linear model and learning parameters of this model from a single foggy image. Berman et al. [7] find that it is useful to be able to estimate haze-free image colors by using hundreds of distinct colors and propose non-local prior according to this. However, these priors are not specialized for QR code recognition and would not perform well in such scenarios.

With the help of rapid development of deep learning, a large number of CNN-based algorithms [8]–[12] are presented by generating broad scale training databases. In contrast to traditional algorithms, CNN-based algorithms possess better effectiveness and higher robustness. These algorithms try to directly recover the intermediate transmission map or the ultimate clear picture. In [8], a multi-scale deep neural network is proposed by learning the connection between foggy pictures and their corresponding transmission maps.

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Cai et al. [9] show a trainable end-to-end network that can predict the medium transmission map. This network can be directly utilized to recover a clean image from a hazy one. Li et al. [10] propose a neural network which can straightforward generate clean images from input hazy ones without estimating global atmospheric light and transmission matrix. Zhang et al. [11] propose a neural network and it can jointly learn the global atmospheric light, the transmission matrix and dehazing simultaneously. Ren et al [12] merge white balance, contrast enhancing and gamma correction to adopt a novel fusion-based strategy in order to yield dehazed results.

For QR code recognition, image binarization has always been an indispensable part of image preprocessing process. On the one hand, if the threshold is reasonably opted according to actual processing situation, important information about the image can be well saved after binarization. On the other hand, after separating the gray value into only two values, the amount of information data of QR code images can be greatly reduced. The efficiency of subsequent recognition processing and decoding can be improved obviously.

Otsu's algorithm [13] is most widely applied in various fields. This method can select the optimal threshold in order to maximize the separability. However, Otsu's method cannot be well used in many complex environments because it is noise-sensitive. Wellner [14] reports a fast-adaptive thresholding method which uses the midpoint as local threshold. Bradley et al. [15] propose adaptive thresholding by using integral image technique. It is only a simple extension of Wellner's method and well-suited for real time adaptive thresholding.

In this paper, we propose a new algorithm for QR code recognition in complex foggy environments, in which a dehazing method is first utilized to obtain clear images and then an improved adaptive thresholding technique is applied to obtain binary results. We collect a set of benchmark of QR code images in heavy foggy conditions for testing our proposed algorithm. To reveal the performance of our proposed algorithm, it is compared with some preceding methods on our own benchmark. Ablation comparison and experimental results demonstrate our proposed algorithm can achieve superior performance both qualitatively and quantitatively. This implies that our proposed algorithm could be used in dense hazy environments and improve the robustness of QR code recognition.

Our approach includes these following steps: (1) Image enhancement method used to respectively enhance the red, green and blue (R, G, and B) channels. Contrast is also increased with this method; (2) Dehazing method which removes haze to obtain clear QR code images; (3) Improved adaptive thresholding algorithm which is applied to obtain binary images. This would help us decode QR code images more accurately; (4) QR code decoding.

The remainder of this paper is structured as follows. Our proposed method is presented in Section II. Ablation comparison and experimental results are discussed in Section III. In the end, in Section IV, conclusions are introduced.

(a) (b)

Fig. 2: Original and Hazy QR code images: (a) original image. (b) hazy image.

(a) (b) (c)

Fig. 3: Intelligent Mobile Robot: (a) Automated Guided Vehicle (AGV) in large warehouses (b) Large storage robot (3)Turtlebot platform in our own lab

II. DEHAZING AND IMPROVED ADAPTIVE THRESHOLDING

Research on intelligent mobile robot platforms has traditionally been a hotspot in the field of robotics [16]. During the past several decades, this technology has been performed in the storage progress, as shown in Fig. 3. Here, we will propose a QR code recognition algorithm which would be used on an intelligent mobile robot of hazardous chemicals warehouses. The overall structure of our algorithm is shown in Fig. 4.

Here, image enhancement method is presented at the beginning. After that the architecture of dehazing method is introduced. Dehazing method is applied to train and test our own database and obtain clear QR code images. Finally, improved adaptive thresholding method using integral image technique is given.

A. Image Enhancement

Foggy conditions could decrease the contrast of QR code images. So, contrast-limited adaptive histogram equalization (CLAHE) [17] is utilized to increase their contrast at the beginning. CLAHE is an effective local contrast enhancement tool and it can enhance local details of the whole picture. CLAHE is originally modified by adaptive histogram equalization. The contrast amplification is limited in order to reduce noise by clipping the value of histogram before computing the cumulative distribution function. Cliplimit, which is defined by the value where the histogram is dealt with, relies on the normalization of the histogram. It also makes a close connection with the size of surrounding area.

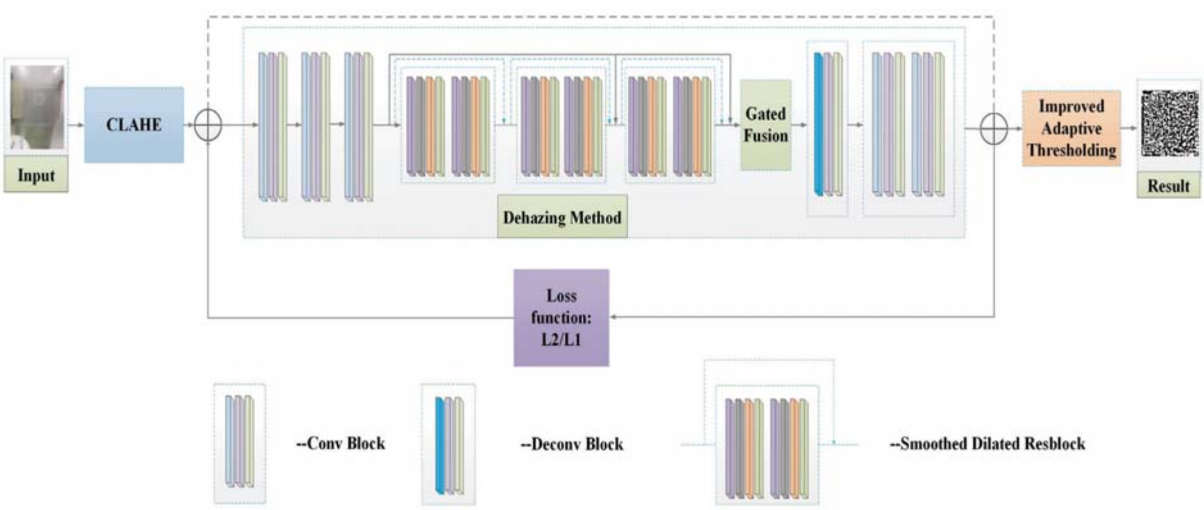

Fig. 4: The proposed Algorithm Structure. It includes CLAHE, Dehazing Method and Improved Adaptive Thresholding.

By using one thousand or more cliplimit, redistribution of histogram bin values which would lead to an effective cliplimit bigger than the set limit could be forbidden. The actual cliplimit is computed via

$$N_{CL} = N_{CLIP} \times N_{average}, \quad (1)$$

where $N_{average}$ represents the average number of pixels and N_{CL} is actual cliplimit function result.

In order to generate enhanced results, interpolating gray level mapping is performed. During this process, we apply pixel clusters and mapping process, after that each of mapping tiles in the image region will partly overlap. Mapping process is applicable to each pixel and interpolating is conducted between that to obtain enhanced pixel. We repeat this process over the entire image to obtain final enhanced one.

B. Dehazing Method

QR code images would suffer from limited visibility and low contrast because of fog. Fog is independent of scene radiance and adds additional components to QR code images. Owing to this, the structure of QR code images may be destroyed and this will make them not directly to be decoded. QR code images degradation influenced by fog increases according to the distance from the camera.

Gated Context Aggregation Network (GCANet) [18] is originally proposed to straightforward restore final dehazed image from a hazy one. Here, we modify GCANet to generate clean QR code images. In this paper, we do not distinguish haze, fog, smoke and directly use the term dehazing for simplicity. The atmospheric scattering model which has been widely used in previous single-image dehazing tasks is described via

$$I(x) = J(x)t(x) + A(1 - t(x)), \quad (2)$$

where x represents pixels in hazy graph, $I(x)$ is input hazy image, $J(x)$ is clean image that would be recovered. Here, $t(x)$ and A depict the transmission matrix and the global atmospheric light respectively. The parameter $t(x)$ is defined via

$$t(x) = e^{-\beta d(x)}, \quad (3)$$

where β depicts the atmosphere's scattering coefficient and the distance between camera and the graph is represented by $d(x)$.

Modified GCANet applies three convolution blocks to be the encoder module, one deconvolution block with stride $\frac{1}{2}$ used to upsample the feature map and two convolution blocks used to transform the feature maps back to QR code picture space to obtain the ultimate objective haze residue. Some smoothed dilated resblocks are applied in this network to aggregate context information without gridding artifacts. Several residual modules are also embed to enhance its learning capacity. These residual blocks' dilation rates are respectively (2, 2, 2, 4, 4, 4, 1) and the channel number is set bo be 64 of all the convolutional blocks to balance performance and runtime.

In contrast to original GCANet, we change instance normalization layer of all convolution blocks into batch normalization layer in order to increase the efficiency of training. For convolutional layers of Modified GCANet, batch normalization respects rules of convolutional neural network. By applying this, different elements of the same feature map, even located in different positions, are normalized using the same method. To fulfill this purpose, all the activations are normalized at the same time in a minibatch over all locations. Too-high learning rates may cause the gradients which explode or disappear. Because of this, Modified GCANet always gets stuck in poor local minima. Batch normalization can also solve these problems.

Fusing features is a significant process for Modified G-CANet to perform both low and high standard missions. Here, a gated fusion sub-network which comprises a simple convolutional network with kernel size 3×3 is used to merge features from different levels. This network has an input which is concatenation of different levels L_1, L_2, L_3 and its out channel number is 3. First, three different features from different levels L_1, L_2, L_3 are extracted and sent into the network. From this, three important weights Y_1, Y_2, Y_3 are obtained. Finally, three features are linearly combined via

$$\begin{aligned} &(Y_1, Y_2, Y_3) = \Gamma(L_1, L_2, L_3), \\ &F_0 = L_1 \times Y_1 + L_2 \times Y_2 + L_3 \times Y_3, \end{aligned} \tag{4}$$

where Γ shows the process that three important weights Y_1, Y_2, Y_3 are computed from different levels L_1, L_2, L_3 through the gated fusion sub-network. F_0 will be sent into the decoder module and the haze residue will be available from here.

The evaluation standards of dehazing methods are generally Mean Square Error (MSE). The loss function of Modified GCANet has a little difference with MSE. The learning target of Modified GCANet is the residue between input hazy QR code images and groundtruth images

$$\begin{aligned} &r = B - A, \\ &\hat{r} = GCANet(A), \\ &\zeta = \|\hat{r} - r\|^2, \end{aligned} \tag{5}$$

where $\hat{r}$ and r are predicted haze residue and ground truth respectively. In the process of experiment, $\hat{r}$ would be added onto the foggy QR code images to obtain ultimate estimated clear ones.

C. Improved Adaptive Thresholding

Separating the pixel of each QR code image into only two values can reduce the amount of information data and save vital information simultaneously. So, we need to change original colored QR code pictures into binary ones. Improved adaptive thresholding method using integral image technique is applied here to fulfill this purpose by modifying [19]. First, QR code image is separated into two different intensity regions. Then every pixel of QR code image is classified as white or black.

The integral image is an excellent technique which can accelerate area calculation. This mathematical model can be expressed via

$$I(a,b) = \sum_{a' \leq a,\ b' \leq b} i(a', b'), \tag{6}$$

where I represents integral value and i is used to depict the intensity at any point (a,b). Meanwhile, the fast calculation of the integral image could be computed straightforward via

$$I(a,b) = f(a,b) + I(a-1,b) + I(a,b-1) - I(a-1,b-1), \tag{7}$$

where $f(a,b)$ represents real numbers of pixels such as pixel intensity and $I(a,b)$ is used to represent the location in the original grayscale image.

After that, each pixel is classified by the following two steps. First, within a moving $S \times S$ window, R_s, which is the sum of pixel values over a rectangle R, is determined. In that way, the size of the window which relies on image's width W is also determined. Unlike [15], possibly maximum width of the window is set as 1/64 of W. R_s is defined via

$$R_s = I(a_2,b_2) - I(a_1,b_2) - I(a_2,b_1) + I(a_1,b_1), \tag{8}$$

where $a_1, a_2 = a \pm \frac{S}{2}$ and $b_1, b_2 = b \pm \frac{S}{2}$. Here, R_s represents a local threshold. On the original grayscale image, R depicts the shadow area.

The number of pixels in R is adopted via

$$C = (a_2 - a_1) \times (b_2 - b_1). \tag{9}$$

The description of adaptive thresholding is represented via

$$i(a,b) \times C \leq R_s \times (1 - T), \tag{10}$$

where T depicts a percentage value. In this process, if each pixel's value is lower than the local threshold, we set it to black, on the contrary we set it to white.

Foggy conditions could increase the intensity of the affected region of QR code images and cause important information lost. Therefore, the original image should be classified into two different intensity regions: one with high intensity and the other with low intensity. To fulfill this purpose, the sum over all the rectangle region is applied to compute a local mean which would be compared with each pixel of the entire graph utilizing the following condition

$$R_s \leq C \times (M + sd), \tag{11}$$

where M and sd depict entire image's mean value and standard deviation respectively. By utilising the above expression, a pixel is classified whether in low or high intensity region. After that, this pixel is binarized. Values in high intensity region are computed by using supplement-grayscale graph with the formula

$$R_s' \times (1 - T) < i'(a,b) \times C, \tag{12}$$

where i' represents the value of supplement-grayscale image at any point (a,b) and Rs' is the Rs at any point (a,b) which is also calculated from here. If the right formula is T percent higher than pixel of Rs', we set it to black, on the contrary we set it to white.

On the other hand, for a pixel in low intensity region, the values' local mean within R region is applied to compare each pixel's value in order to classify each pixel. All values are computed from the original grayscale image via

$$R_s \geq C \times i(a,b). \tag{13}$$

The pixel would be set to white if its value is higher than or equal to surrounding pixels' local mean, otherwise we set it to black. Unlike [19], C is equivalent to 1.

By using this algorithm, a dehazed QR code image is transformed into a binary one. It helps us decode QR code image straightforward and conveniently.

Fig. 5: Experiment Process. Row 1: Groundtruth QR code images. Row 2: Hazy images. Row 3: Image Enhancement. Row 4: Dehazing Method. Row 5: Improved Adaptive Thresholding. Row 6: Information of QR code.

III. EXPERIMENTS

A. Dataset

For testing our proposed QR code recognition algorithm, we collect a set of benchmark of hazy QR code images. Examples of original images are in the first row and their corresponding hazy ones are in the second row in Fig. 5. First, QR code images of hazardous chemicals are created providing the following information: name, shape, CAS number and dangerous class. There are four classes of danger of all hazardous chemicals: flammable, explosive, corrosive and toxic. Then 220 pictures of QR code are captured in a dense hazy environment applying some fog-creating machines. From these pictures, we select all which cannot be directly decoded by the “Scan QR code" function of Wechat and our own decoding program.

B. Implementation Details

At first, image enhancement method is employed to get enhanced QR code image. As shown in the third row of Fig. 5, contrast of all QR code images increase obviously. Meanwhile, visibility of these QR code images has also been improved. Both contrast enhancement and better visible quality results can be obtained during this process. Our processor possesses Intel Xeon(R) Gold 6140 CPU@2.30GHz$\times$46, Quadro P6000 and 125.6 GB memory.

After that, 500 hazy and 50 real outdoor images from SOTS subset which is provided by RESIDE [20] are utilized to train our dehazing algorithm. QR code images dataset which contains 220 pictures is utilized as testing set. Dehazing method is applied to obtain a training model and this model is applied to get dehazed results, which are shown in the fourth row of Fig. 5. All these training experiments are performed with the default batch size 4 and epoch 1000.

Then improved adaptive thresholding method is used to receive binary images, as shown in the fifth row of Fig. 5. We use 1/64 of W as image’s maximum window’s width S and obtain binary results of all QR code pictures. Results of obtaining binary images are decoded and the number of all the accurately decoded ones is calculated. Statistical results are displayed in Table 1. Information about what these QR code images contain is presented in the sixth row of Fig. 5.

According to Bradley’s method [15], window’s maximum width S is 1/8 of W. However, we find that when window’s maximum width S is 1/8 or 1/256 of W, QR code images cannot be directly decoded. Some small-scale experiments are performed and when 1/64 of W is applied as image’s maximum window’s width S, better results can be obtained. Process of these experiments is shown in Fig. 6.

C. Ablation Comparison

Different dehazing methods may influence quality of QR code recognition because the process of dehazing would cause important information what these QR code contain lost. Here, we compare decoding accuracy of several different dehazing algorithms including traditional and CNN-based methods: (a) Color-Attenuation-Prior & adaptive thresholding; (b) DCP & adaptive thresholding; (c) Adaptive Thresholding; (d) AOD-Net & adaptive thresholding; (e) Our proposed algorithm. PAD-Net is modified from AOD-Net. Comparison results are located in Table 1.

We can find that traditional dehazing algorithms may lose significant information of QR code. On the contrary, CNN-based dehazing algorithms could save more information and

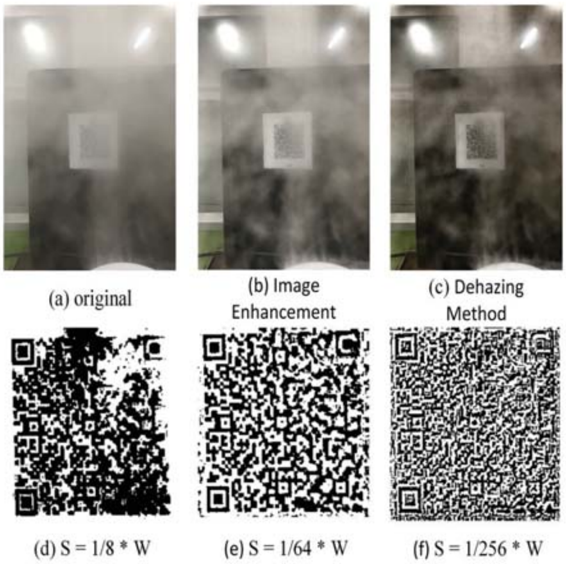

Fig. 6: The comparision results of S: (a) Original image. (b) After Image Enhancement. (c) After Dehazing Method. (d) $S = \frac{1}{8} \times W$. (e) $S = \frac{1}{64} \times W$. (f) $S = \frac{1}{256} \times W$. (e) could be directly decoded, (d) and (f) could not be directly decoded.

TABLE I: Accuracy Comparison Results

Algorithm	Total Pictures	Decoding Pictures	Accuracy(%)
Color Attenuation Prior [6] & Adaptive Thresholding [19]	220	72	32.73
DCP [4] & Adaptive Thresholding	220	74	33.64
Adaptive Thresholding	220	90	40.91
AOD-Net [10] & Adaptive Thresholding	220	92	41.82
Proposed algorithm	220	108	49.09

be more robust in complex environments. It can be found that QR code recognition accuracy of our proposed algorithm achieve the best result among all these algorithms, as shown in Table 1. This means that our proposed algorithm is more adapted to sophisticated hazy environments.

IV. Conclusions

This paper proposes a robust QR code recognition algorithm based on dehazing and improved adaptive thresholding method in complex foggy conditions. First, original images of our hazy QR code database are enhanced. Contrast and visibility of them are increased at the same time. Then dehazed results are obtained by using high-quality dehazing method. After that improved adaptive thresholding approach is exploited to obtain binary images. Finally, QR code of these pictures is decoded and recognition performance of different dehazing algorithms is compared. We collect a set of benchmark of QR code images in dense foggy conditions for testing our proposed algorithm. Experimental results demonstrate that our proposed algorithm can achieve superior recognition performance. For QR code, our work can improve its recognition robustness and make it work well in dense hazy environments. In the future, we will continue to improve the performance of our algorithm and extend it to more fields.

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