Integrating QR Code Characteristics into Super-Resolution Method

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***Abstract*—QR code images are used to store URLs and account information. We can quickly access coded data by scanning QR code images with our smartphones. Although these images are widely used, their readability can sometimes be affected by blur or noise. In such cases, a method to read these degraded QR code images is needed. There are several methods to convert unreadable QR code images into readable ones. However, these methods are structural modifications of simple super-resolution models. In this paper, we propose a super-resolution model for QR code images that takes advantage of their unique characteristic. The QR code image can store specific data, and the value near the center of the module in the QR code image is crucial for this storage function. Therefore, we propose a super-resolution model that focuses on removing noise around this area in the QR code image. The effectiveness of the proposed method is confirmed by determining the readability of the generated QR code images.**

***Index Terms*—super-resolution, QR code image, SRCNN**

I. Introduction

QR code images are used in a wide range of fields, such as electronic payment and ticketing. These images consist of black and white boxes, referred to as modules. By rearranging these modules, specific data can be embedded in the QR code image. This data can be accessed by simply holding a camera over it. However, QR code images may sometimes be unreadable due to the addition of noise and blur. Therefore, QRCNN [1] has been proposed to convert unreadable QR code images into readable ones. QRCNN aims to remove noise and blur by using an image super-resolution method. However, QRCNN does not consider the characteristic of QR code images. It is restricted to altering the model structure of a standard super-resolution model known as SRCNN [2].

We propose a super-resolution model specifically designed for QR code images, taking advantage of their unique property. This unique property is that the area near the center of the module is critical for decoding the data embedded in QR code images. Therefore, our method aims to efficiently recover that area in QR code images degraded by blurring. Additionally, to avoid increasing the number of parameters, the model structure of the conventional method is kept the same, but the training method is modified. The goal of this method is to improve the performance of super-resolution models for QR code images without increasing computational complexity. In experiments, we compare our proposed method with QRCNN and SRCNN to confirm its effectiveness.

II. Related Work

A. SRCNN

SRCNN is the first super-resolution model using CNN, which consists of three convolutional layers. It uses neural networks to generate high-resolution images, unlike rule-based algorithms such as nearest-neighbor and bicubic interpolation [3]. In SRCNN, a low-resolution image is input and upscaled using the bicubic interpolation. It then adjusts the pixel values using neural networks to output a high-resolution image. This model is trained to minimize the mean squared error (MSE) between output and original images. The loss function used for training the model is expressed as follows:

$$L = mse(x_{gt}, x_{output}). \tag{1}$$

In (1), x_{gt} is the ground truth image and x_{output} is the output image of the model. mse represents the MSE function.

B. QRCNN

QRCNN is a model designed to transform unreadable low-resolution QR code images into readable high-resolution ones. It consists of three convolutional layers, two-pixel shuffle layers, and two activation functions. By adjusting the kernel size of the convolutional layers, this method proposes a super-resolution method for QR code images that is more effective and lightweight compared to SRCNN. The training process for this model involves resizing QR code images and adding Gaussian blur and noise to generate unreadable QR code images. These unreadable images are used as input for QRCNN, which is trained to output high-resolution QR code images. The loss function is defined in (1).

III. Proposed Method

We propose a super-resolution model that takes advantage of the characteristic of QR code images. The model structure of our method is based on that of QRCNN. The training process

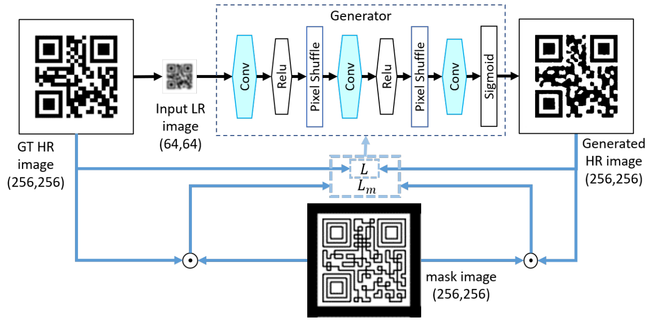

Fig. 1. Training process of our proposed model.

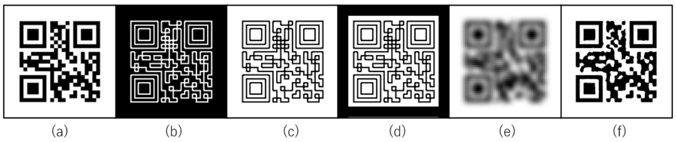

Fig. 2. Example of a QR code image and its corresponding mask images. (a) is the ground truth, (b)is the edge of the QR code image, (c) and (d) are the mask images utilized in the training process,(e) is the blurred image, and (f) is the generated image.

of the proposed method is shown in Fig. 1. QR code images are made up of black and white modules, and the values near the center of the modules are crucial for decoding the data they contain. Therefore, we train QRCNN with weight on the center of the modules. By using a mask image in the training process, we can weight on the local portions of the image. To create the mask image, we apply canny edge detection to the original QR code image shown in Fig. 2(a). Then, we utilize morphological transformation to expand the edge regions. The mask image obtained from this process is shown in Fig. 2(b). The black and white of this mask image is inverted to create the image shown in Fig. 2(c). This inversion is performed as follows:

$$m' = 1 - m. \tag{2}$$

In (2), m is the binary mask image representing an edge area in the QR code image. m' is the inverted binary mask image.

In addition, the mask image shown in Fig. 2(d) is also prepared. This image is created by filling the margins of the image in Fig. 2(c) with black. The loss function used for training our model is expressed as follows:

$$L_m = mse(x_{gt} \odot mask, x_{output} \odot mask) + L. \tag{3}$$

In (3), the variable $mask$ is the binary mask image. The other variables and functions are the same as those shown in (1). The MSE loss in the mask region in the image is added to the loss function in the conventional method.

IV. Experiment

We prepare 1000 QR code images [4] for training the proposed model. To generate unreadable low-resolution QR code images, we first downscale QR code images using the bicubic method and then apply Gaussian blur. An example of a low-resolution QR code image after the application of Gaussian blur is shown in Fig. 2(e). In this experiment, the kernel size of the Gaussian blur is fixed at 7, and the standard deviations are 1.60, 1.65, and 1.70. These unreadable QR code images are used as input for our proposed model.

We use SRCNN and QRCNN as comparative methods. These conventional models are trained in the same way as the proposed model. The official implementation of QRCNN does not have enough epochs used for training. Therefore, we increased it to 40 epochs in our training process.

TABLE I
Result of the readability [%] of blurred QR code images.

Method	standard deviation		
	σ=1.60	σ=1.65	σ=1.70
Blurred QR code image	0.0	0.0	0.0
SRCNN [2]	42.4	26.4	19.0
QRCNN w/o mask [1]	98.2	72.6	29.4
QRCNN w/ mask (c) (ours)	99.6	82.2	33.2
QRCNN w/ mask (d) (ours)	**99.8**	**83.0**	**33.8**

Using 100 QR code images, we evaluate the readability of the output images generated by SRCNN, QRCNN, and our method. An example of an image generated by the proposed model is shown in Fig. 2(f). The readability of the input low-resolution images is also measured. QR code images are determined to be readable when the information detected in the generated QR code image matches the information detected in the original one.

The results are shown in Table I. Training the model with mask images improves the readability of the output QR code images. These results indicate that the information near the edges of the QR code modules is less important. Additionally, the marginal areas of the QR code image are also less significant, as the best performance is achieved with mask image (d). Therefore, restoring the values near the center of the modules is crucial for the super-resolution of the QR code image.

V. Conclusion

In this paper, we propose a super-resolution model for QR code images that exploits the unique characteristic of these images. Experimental results show that the proposed method outperforms conventional methods in terms of the readability of the generated QR code images. For future research, it is necessary to create a model that is robust to changes in image tilt and color, assuming actual use cases.

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