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Quick response barcode deblurring via doubly convolutional neural network

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Abstract Various image preprocessing applications for two dimensional (2D) barcode involve reversing the degradation operations (e.g. deblurring). Most of the previously proposed deblurring approaches focus on the construction of suitable deconvolution models, which have shown significant performance at laboratory level. However, the model-based image deblurring solutions might not work well in practical scenarios. To deal with this problem, we propose a convolutional neural network (CNN) based framework to tackle the parameter-free situation for 2D barcode deblurring. The proposed solution leverages the deep learning technique to bridge the gap between traditional model-based methods and requirement of reversing the blurry 2D barcode images. Experiments on practically blurred quick response (QR) barcode images demonstrate that the proposed approach achieves the superior performance in comparison with state-of-the-art model-based image deblurring approaches.

Keywords Image Processing · Deblurring · Convolutional Neural Network · 2D barcode

1 Introduction

QR barcodes [35] (as shown in Fig. 1), which were invented by the Toyota subsidiary Denso Wave in 1994 and were originally used to track vehicles during the manufacturing process, are a typical category of matrix 2D bar codes. QR barcode is consisted of a printed square pattern of small black and white squares that encode data which can be scanned into a computer system. The black and white squares within it can represent numbers from 0 to 9, letters from A to Z, or characters in non-Latin scripts such as Japanese kanji [13]. There have been different versions of QR barcodes proposed with different information capacity as shown in Fig. 2. QR barcodes are applied widely due to a great deal of advantages, including small tag, large data capacity, reliability, and swift scanning, it plays an significant role in a variety of practical applications,

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e.g. industrial automation and manufacturing systems [30], public transportation [34], public hygiene [16], cell phone based application [31, 48], and product tracing [21, 46].

At present, QR code based applications can obtain adequate imaging quality with recent development of optical hardware [44]. However, the readability of the QR code images may still be degenerated during imaging procedure due to various issues including out-of-focus blur [32] and motion blur [6]. These artifacts can not only defeat many existing algorithms but also create challenges in the QR code reading and decoding process. As it is designed for the contained information to be decoded at high speed [12], QR code is extensively exploited for product tracing in industry production line. Therefore, the deblurring of QR code images becomes one of the most fundamental and important issues in industrial automation for manufacturing.

According to the presence of additive hardware, current deblurring methods for QR barcode images can be categorized into two groups: hardware based techniques and image based processing strategies. The first group enhances the performance of QR decoding systems by using complementary hardware [14]. However, the additive hardware components inevitably increase the overall cost of the corresponding barcode reading equipment. In contrast, the second group reverses the degraded QR barcode image by leveraging various deblurring algorithms [5, 10, 12, 43] without the extra hardware. Most of these methods could be attributed to the deconvolution framework, which has been exploited in plenty of image deblurring applications [4, 22, 23, 26, 29, 36, 41], several of which have been validated to work well on QR barcode images.

In the last decades, deep learning has shown its great ability in plenty of fields in information processing [2, 15, 27]. And its performance has been testified in various applications, e.g. speech recognition [8, 9, 11], music processing [3], object recognition [2, 15], and natural language processing [7, 49]. CNN, which is regarded as one of the most significant deep learning models, has attracted much attention in a large variety of image processing tasks [17, 19, 20, 25, 33, 37, 39, 40, 42, 47]. However, we noticed that the performance of deep learning models for deblurring QR barcode images in industrial automation still needs to be explored.

In this paper, we present an effective and efficient image deblurring tool for recovering the blurry QR barcode images (presently the blurry effects mainly includes the out-of-focus blurred and motion blurred), which is accomplished by using a novel CNN architecture adapted to the characteristics of QR barcode. Our approach is data driven and free from hand-crafted image features. It leverages a data training process to extract multi-scale image features automatically

Fig. 1 The QR code produced by 360 Total Security [38]

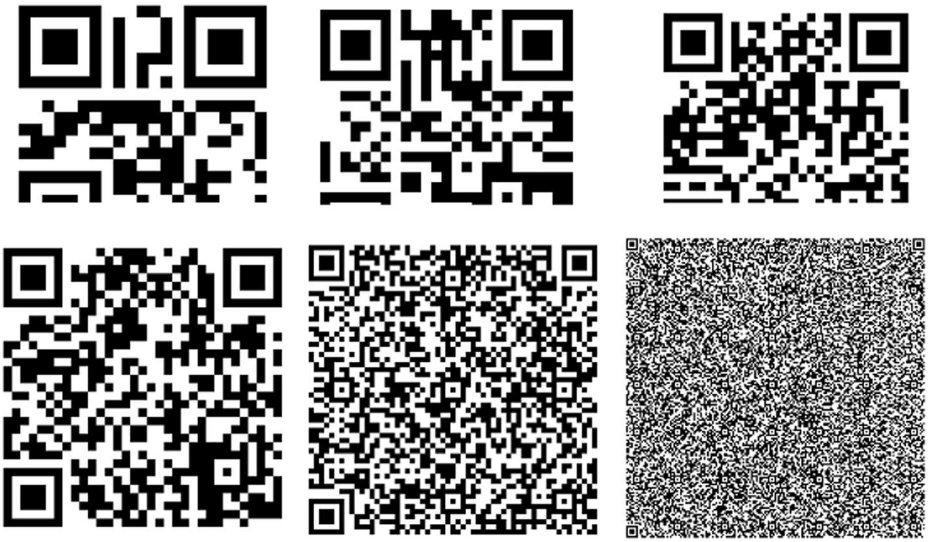

Fig. 2 Different versions of QR codes

which could combine both the local and global characteristics in the QR barcode images. The mapping between the QR barcode and its corresponding blur kernel, which is learned from the above-mentioned features, offers a function to automatically specify the latent QR barcode given an input blurry QR barcode image. In our newly proposed CNN architecture, the traditional convolution layer is modified into a doubly convolutional layer. To note that the proposed doubly convolutional layer can guarantee the output blur kernels are continuous versions of each other. And the other details of the doubly convolutional layer will be fully discussed in Section 2. The experimental results for practical QR barcode images degraded by different blur kernels show that the proposed CNN architecture produces an impressive accuracy of more than 99%, which is considerably better than most of the conventional techniques.

Our work offers at least five significant contributions as listed below:

(I) To our best knowledge, this is the first attempt to introduce deep learning strategy into the image deblurring of QR barcode.
(II) We propose a novel CNN architecture with doubly convolutional layer which is adapted to the characteristics of QR barcode.
(III) Different from the original convolution layer in common CNN architectures, a doubly convolutional layer is presented.
(IV) We show that a combination of local and global features of the QR barcode images can significantly improve the accuracy of image deblurring.
(V) Our approach performs with an impressive superiority in comparison with state-of-the-art deblurring approaches.

The rest of this paper is organized as follows. In Section 2, we present the details of our proposed QR barcode image deblurring approach including the architecture of the convolutional neural network and the newly presented doubly convolutional layer. Section 3 shows the experimental results and its corresponding analysis. In Section 4, we present the conclusion and our future work.

2 Our method

In the proposed CNN architecture, one deconvolution process is included to inverse the degraded practical QR barcode image. Thus, we firstly discuss the blurring model and deconvolution operation used in our method before we introduce the proposed method.

2.1 Deconvolution operation in our method

In our method, the fundamental processing element of the deblurring is the blurry QR barcode image. And each of the input blurred images is viewed as the result of corresponding latent image convolved with an out-of-focus or motion blur kernel. Then, our proposed CNN based method is exploited to extract the most suitable blur kernel, with which the corresponding latent image can be output by our proposed CNN architecture.

The image blurring model in our proposed method could be expressed as Eq. (1):

$$I = O \otimes K \tag{1}$$

where Idenotes the blurred QR barcode image, Ostands for the corresponding latent image, $\otimes$ is convolution operator, and Kdenotes the corresponding blur kernel.

The convolution operation in Eq.(1) can be transformed to frequency domain, which is expressed by Eq.(2):

$$F(I) = F(O).F(K) \tag{2}$$

where $F(\cdot)$ denotes the discrete Fourier transform (DFT) operation, and the symbol $\cdot$stands for the element-wise multiplication operator. In frequency domain, the latent image O can be expressed by Eq.(3):

$$O = F^{-1}(F(I)/F(K)) = F^{-1}(1/F(K)) \otimes I \tag{3}$$

where $F^{-1}(\cdot)$ denotes the inverse discrete Fourier transform (IDFT).

It can be explained that the deconvolution operation equals to the latent image convolved with a deconvolution kernel, expressed by Eq.(4):

$$O = K^{-1} \otimes I \tag{4}$$

where K^{-1} denotes the deconvolution kernel corresponding to the convolution kernel in Eq.(1).

After obtaining the output blur kernel through our proposed CNN, the latent image can be calculated with Eq.(2), Eq.(3), and Eq.(4), successively. It is worthy notable that the latent image O is difficult to restore, which is due to the useful information loss occurs during the degradation procedure. In order to complement the lost information, existing deconvolution methods commonly employ specific priori hypothesis for deblurring OCT image, e.g. Gaussian distribution [18] and natural image statistics [28]. But these priori hypotheses, which are suitable for natural image, may not be applicable to QR barcode images since they do not obey Gaussian distribution or natural image statistics. In the contrary, in the proposed CNN based deblurring technique, we present a data-driven CNN architecture to produce suitable blur kernel without any priori hypothesis on the characteristics of the blurry images.

2.2 Architecture of our proposed convolutional neural network

The proposed CNN architecture is given in Fig. 4, where the objective function can be expressed by Eq.(5):

$$\min\left[\frac{1}{N}\sum_{i\in N}\left\|F^{-1}(1/F(K))\otimes I-O\right\|_2^2\right] \tag{5}$$

where N denotes the number of input blurred QR barcode images, F^{-1} and F respectively represents IDFT and DFT, K is the blur kernel which is the output of our proposed CNN architecture, I denotes the blurred image, and O indicates the corresponding latent image.

Specifically, the blurry QR barcode images are processed by following sequential phrases:

- Convolutional combined with the Rectified Linear Units (ReLU) layer, in which the features embedded in the input image are extracted initially. In order to extend the parameter sharing efficiency of CNN, we replace the independent convolutional filters in the convolution layers by a set of filters that are translated versions of each other, which is implemented by a two-step convolution operation or so-called doubly convolutional layer as shown in Fig. 3.
- Average-pooling layer, the extracted image features are down-sampled and smoothed. In the proposed CNN architecture, there are two average-pooling layers. In previous proposed CNN architecture, this kind of pooling layer is exploited to guarantee the existing smoothness among neighboring pixels. It is introduced to keep the smoothness among the neighboring pixels in the output of convolutional layer. In our proposed CNN architecture, these two layers can greatly enhance the smoothness and continuity in latent QR barcode image.
- Convolutional combined with the Rectified Linear Units (ReLU) layer; the features in the input image are extracted furthermore. Same as the first layer in our CNN architecture, this layer is also a doubly convolutional layer with ReLU.
- Average-pooling layer, the extracted image features are down-sampled and smoothed, continually. The function of this layer is the same as the previous average-pooling layer.
- Fully connected combined with ReLU layer, which is used to perform high-level reasoning like neural networks.
- Soft-max layer, is the classifier used to differentiate the blur kernels from each other. With the soft-max layer, this CNN can predict the probability of blur kernel corresponding to the blurred QR barcode image, as expressed in Eq.(6).

$$P(O_i|I_i)=\frac{\exp\left(\left(\omega_k^{layer6}\right)^T\phi_{layer5}(I_i)\right)}{\sum_n\exp\left(\left(\omega_n^{layer6}\right)^T\phi_{layer5}(I_i)\right)} \tag{6}$$

where O_i denotes the input blurred QR barcode image, I_i represents the corresponding latent QR barcode image, ω_k^{layer6} is the weight of k_{th} blur kernel of the fully connected layer, k indicates the index of all of the blur kernels, and ω_{layer5}denotes the 1024-dimensional features existing in the fully connected layer.

Meanwhile, the loss function of the proposed CNN solution is shown as:

$$Loss = \sum -\log(P(\omega_k)|(I_i)) \tag{7}$$

where $P(\omega_k)|(I_i)$ indicates the probability of the k_{th} blur kernel to image I_i correctly classified as l_k.

At the end of the CNN architecture, the deconvolution operation is used to reverse the input blurry image. Therefore, the output of our proposed CNN architecture is the latent QR barcode images.

It is worth noting that not only out-of-focus blur kernels but also motion blur kernels can be extracted by our proposed CNN architecture. Therefore, the proposed architecture can be employed to deblurring both the out-of-focus blurred and motion blurred QR barcode images.

3 Experiments

3.1 Image sampling and the manually degeneration

The objective of our proposed CNN based deblurring method is to extract the most suitable blur kernel corresponding to every blurry image. After obtaining the output blur kernel, the degraded image can be reversed by adopting Eq.(3), which is embedded at the end of our proposed CNN. In order to train the proposed CNN with blurred QR barcode images, firstly we collected plenty of QR barcode images captured from a camera (Canon EOS 760D, Japan) positioned at the production line (Hisense, Qingdao, China). Secondly, we introduced two types of blur kernels, i.e., the out-of-focus blur kernel and the motion blur kernel, to manually degenerate the captured QR barcode images, respectively. In total, we collect 100 different QR barcode images, which are then degenerated by the following out-of-focus blur kernels and motion blur kernels. The blur kernels were added to the captured QR barcode images randomly.

3.1.1 Out-of-focus blur kernels

In the proposed CNN architecture, we choose simple blur kernels to simulate the blurring effect in QR barcode image. The out-of-focus kernels are constructed by the following equation, shown as:

$$K_i = \frac{1}{\pi R_i^2}, \sqrt{i^2 + j^2} \le R \tag{8}$$

where $R_i = n$, $n \in \{11, 12, 13\ldots, 30\}$, K denotes the out-of-focus kernel, R_i denotes the radius of Confusion Circle [1] or blur radius, (i, j) denotes the coordinate of each pixel in a QR barcode image.

Totally, we generate 20 out-of-focus blur kernels of radius from 11 to 30 with interval 1. These out-of-focus blur kernels are shown in Fig. 5.

3.1.2 Motion blur kernels

We choose eighteen motion directions from 0° to 180° with interval 10 (i.e., 0°, 10°, 20°,..., 170°), and 5 motion length from 20 pixel to 30 pixels with interval of 2. Therefore, there are 91

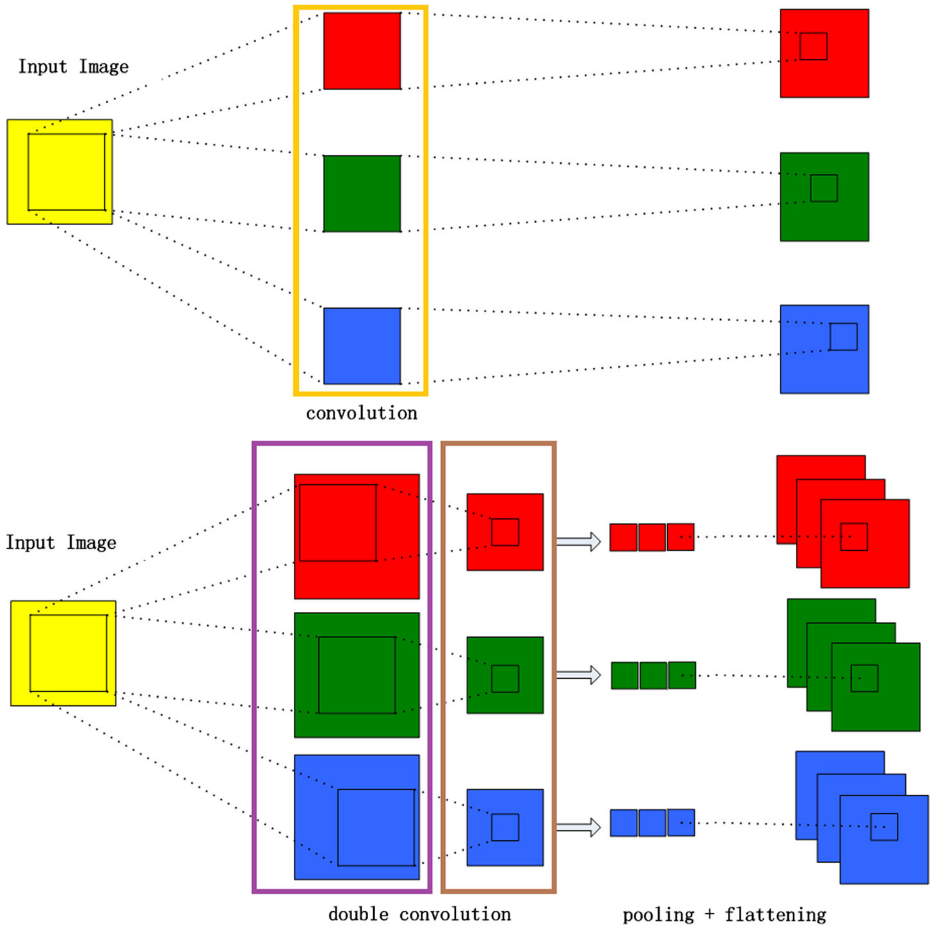

Fig. 3 The structure of a convolutional layer (top) and a doubly convolutional layer (bottom). By adding one extra convolution operation (in the purple rectangle), the independent filters (the yellow rectangle) are changed into translated versions of each other (brown rectangle)

different motion blur kernels generated with these motion directions and motion lengths. These motion blur kernels are expressed as follows:

$$K_i = \frac{1}{L}, \sqrt{i^2 + j^2} \leq \frac{L}{2} \, and \, \frac{i}{j} = -\tan\theta \tag{9}$$

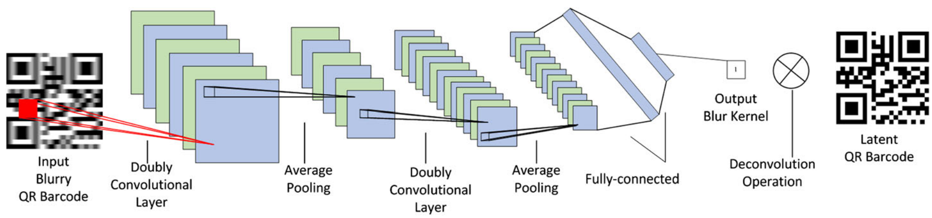

Fig. 4 The architecture of our introduced Deep Convolutional Neural Network

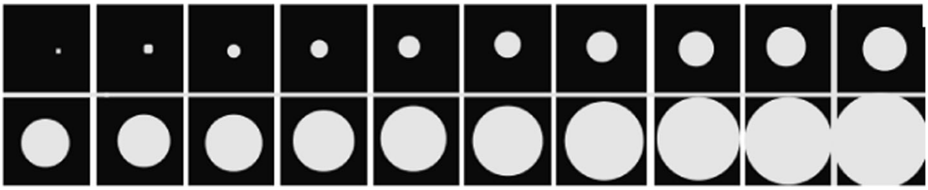

Fig. 5 The introduced Out-of-focus Blur Kernels

where L denotes these 5 different motion lengths, (i, j) is the coordinate of each pixel in a QR barcode image, and θ indicates each motion direction. The motion blur kernels are shown in Fig. 6.

3.2 Training

CNN relies mainly on quantitatively training on blurred images. In order to train our proposed CNN for reversing out-of-focus and motion blurred QR barcode image, we need to prepare numerous pairs of blurred image and the corresponding label of blur kernel. Ten thousands of QR barcode images, obtained from one computer vision system, are chosen as the whole dataset. Six thousands of these images are exploited in the training process of our proposed CNN, the rest of the images are taken as testing dataset. All of the captured images are randomly blurred with the above-mentioned blur kernel, respectively.

In the training process, each pair of blurred QR barcode image and the corresponding blur kernel are regarded as input of the proposed CNN. Translation, rotation, and transformation, are exploited to increase the diversity of input. After the augmentation, our proposed deep CNN is updated with the back propagation mechanism, which calculates the minimization of the image-wise sum of squared difference between the label of predicted blur kernel and the label of ground truth blur kernel.

Training is performed with a high performance GPU and Caffe [19], and it takes 10^6 times of iterative computation. Each computational round in training requires 5–20 s.

3.3 Experimental results and discussion

After the training process we conducted experiments to testify the performance of our proposed CNN. The experimental result of the full testing data is shown in Fig. 7. We obtained that the accuracy of our method reaches to 99.11% after about 3000 iterations. Meanwhile, the training loss of our method decreases to 0.01. (The decreasing process of training loss represents the convergence of the proposed CNN architecture.)

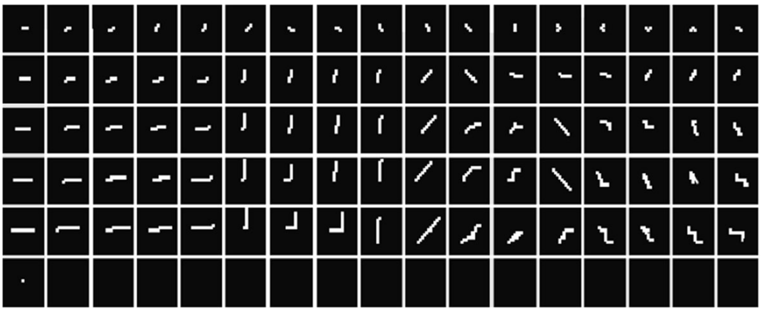

Fig. 6 The introduced Motion Blur Kernels

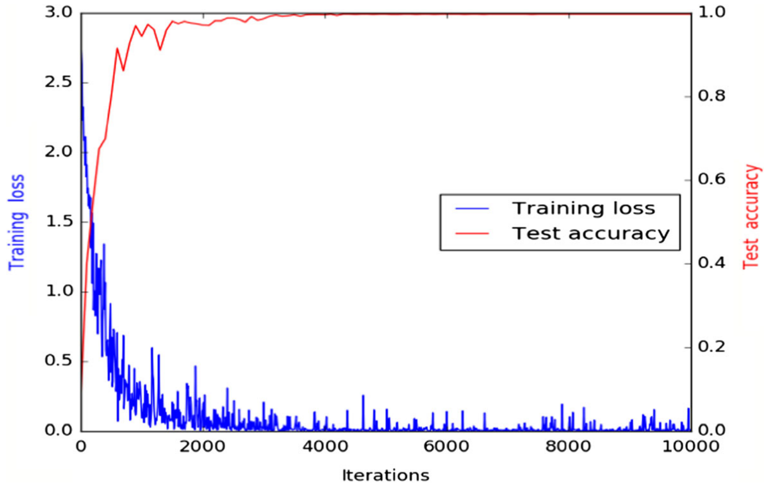

Fig. 7 The accuracy of our proposed CNN architecture

Meanwhile, we conducted the performance comparison between our method and two other base line deconvolution methods, i.e., sparse prior deconvolution [23], Richardson-Lucy deconvolution [45].

To present the performance of proposed image deblurring approach in a reasonable way, PSNR (Peak Signal to Noise Ratio), which is the most widely used image quality evaluation metric, is introduced to measure the performance of state-of-the-art methods and our method. Its definitions can be formulated as follows.

$$PSNR = -10\log\frac{MSE}{K_{\max}^2} \tag{10}$$

where

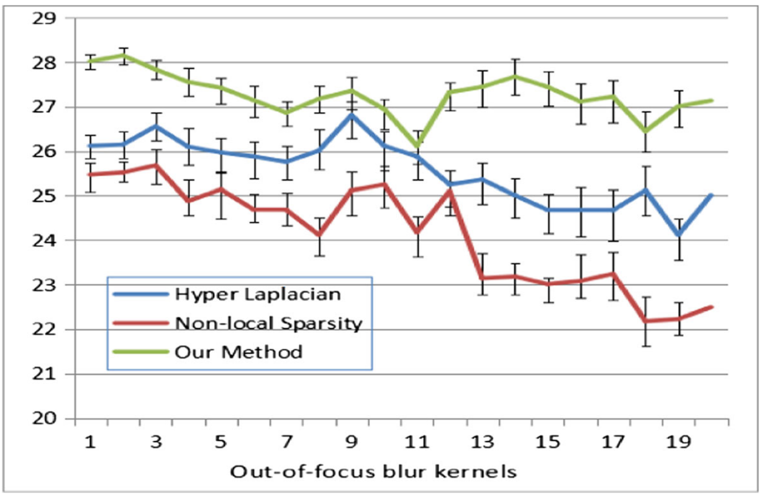

Fig. 8 The PSNR of Out-of-focus Blur Kernels

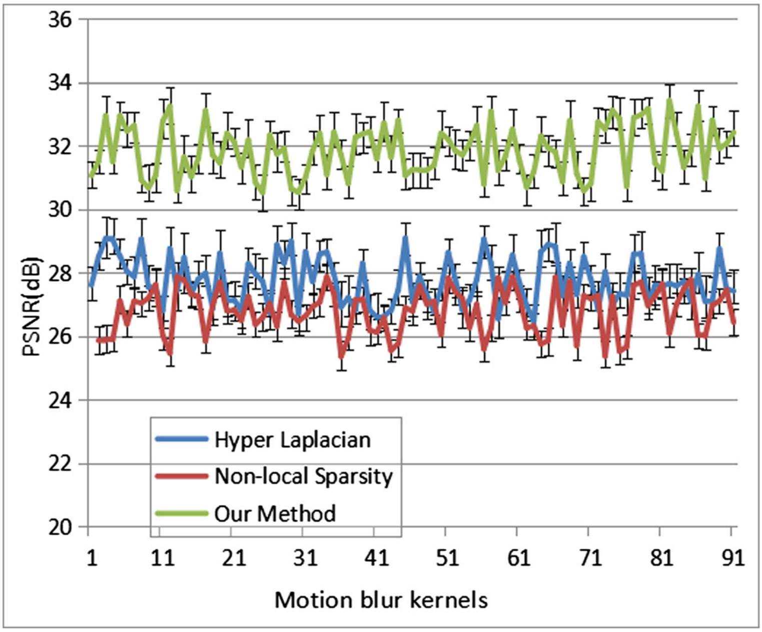

Fig. 9 The PSNR of Motion Blur Kernels

$$MSE = \frac{1}{2|\Omega|} \sum \left(K_p - K_g\right)^2 \tag{11}$$

in Eq.(11), $|\Omega|$ denotes the space of blur kernel, K_p represents the predicted blur kernel, K_g is the ground truth of blur kernel, and K max denotes the maximum size of the blur kernel.

Then we compare the proposed approach and other two baselines [22, 24] on synthetically blurred QR barcode images degenerated by out-of-focus blurred or motion blurred. The PSNR plots of the synthetic out-of-focus blur kernels and motion blur kernels are shown in Fig. 8 and Fig. 9, respectively. As observed, our proposed method performs better than the other two methods in terms of PSNR, including the Average Expectation and Standard Deviation. The performances of the two methods are also shown in Fig. 8 and Fig. 9. As the employment of sparseness, the method [24] achieves better result than the method [22]. Our method, by training on

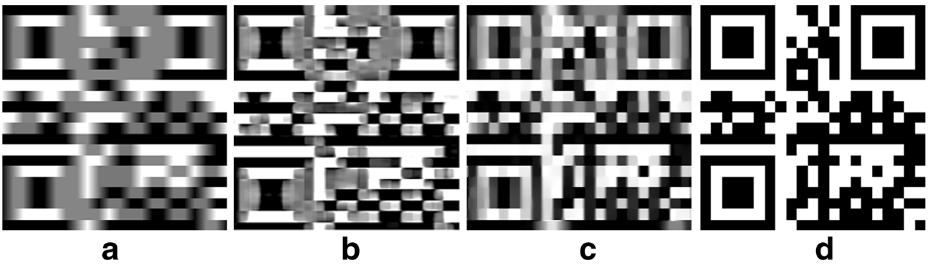

Fig. 10 The motion blurred image and the corresponding deblurred image by state-of-the-art methods and our method. (**a**) Blurred image (motion blurred, length = 21, angle = 0), (**b**) Deblurred image by [22], (**c**) Deblurred image by [24]), (**d**) Deblurring image by our method

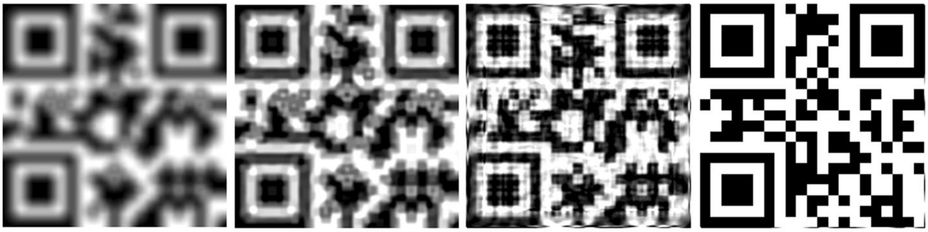

Fig. 11 The out-of-focus blurred image and the corresponding deblurred image by state-of-the-art methods and our method. (**a**) Blurred image (out-of-focus blurred, radius = 9), (**b**) Deblurred image by [22], (**c**) Deblurred image by [24]), (**d**) Deblurring image by our method

numerous blurry QR barcode images with deep learning strategy, produces better result than the other two methods.

The average PSNR results are listed in Table 1, which demonstrates the decent performance of the proposed approach.

Based on the experimental results, we can draw the conclusion that the proposed data-drive method is more effective than other baseline model-based methods. Because model-based deconvolution methods (e.g. fast image deconvolution using hyperlaplacian priors [23] method) assumes that the intensity of the image should satisfy certain distribution (e.g., Gaussian or heavy-tailored), which is not applicable for QR barcode image (it is not natural image). Furthermore, different from baselines, the proposed approach takes the smoothness of latent QR barcode image into consideration.

Figures 10, Fig. 11, show the visual comparison between two deconvolution methods and our proposed method for deblurring the QR barcode images, respectively. The experimental result of the two previous methods in Fig. 10 and Fig. 11 shows that the model-based deconvolution methods would fail if their priors are not suitable for the practical image, e.g. the method proposed in [45] assumes that the image should fit Gaussian distribution, which is not the case in QR barcode image. And our method, which is data-driven, can definitely enhance the performance of deblurring.

Unlike common image deblurring tasks, the performance of QR barcode deblurring method should be evaluated through the readability of the deblurred image. Thus, in order to testify the readability of our method in actual scene, we conducted the comparing experiments between state-of-the-art methods [22, 24] and our method with a QR barcode reading software, Zbar [50]. Table 2 shows the testing results of the two comparing deconvolution methods and our method. Both the visual effects and the readability of our method outperform state-of-the-art methods [22, 24], which show that the inappropriate assumption of priors can heavily degenerate the image deblurring outcome. While our proposed method can avoid the above-mentioned problem by training on quantitative blurry QR barcode images.

Table 1 Comparison of PSNRs with the competing methods

Methods	Hyper-Laplacian [22]	Non-local Sparsity [24]	Our method
Out-of-focus	26.45 dB	24.12 dB	27.27 dB
Motion	27.61 dB	26.61 dB	31.85 dB

Table 2 Comparison of readability with the competing methods

Methods	Hyper-Laplacian [22]	Non-local Sparsity [24]	Our method
Out-of-focus	67.22%	75.18%	97.27%
Motion	71.61%	76.58%	98.85%

4 Conclusion and future work

In this paper, we propose a novel CNN solution to handle QR barcode image deblurring task. To our best knowledge, this is probably the first application of CNN to solve the problem of QR barcode image deblurring. In order to handle the smoothness in QR barcode image, we adopt a newly presented convolutional layer in the proposed CNN architecture. With the training of blurry QR barcode images degenerated by different blur kernels, our CNN based method can be used to reverse both the out-of-focus blurred and motion blurred QR barcode images. To testify the visual effect of our method, we conducted comparing experiments between state-of-the-art deconvolution methods and our proposed method. Furthermore, to verify the readability of our method, we also conducted comparing experiments between state-of-the-art methods and ours with Zbar [50]. Experimental results show that the CNN method outperforms the state-of-the-art deconvolution method to deblurring QR barcode images both in humans' vision and machine vision readability. Through combining all the useful information of input image and deep learning strategy, the proposed CNN solution can dramatically enhance the performance of deblurring QR barcode image.

Meanwhile, we have following important contributions. First of all, this is the first time to introduce machine learning based method into the deblurring of QR barcode image. Secondly, the doubly convolutional layer introduced by our method positively affects the visual effect and readability. Finally, our approach performs with an impressive superiority to both the state-of-the-art image deblurring techniques. The proposed method also has some disadvantages. For instance, we did not take the characteristics of QR barcode image into consideration, which is also the disadvantage of most of the CNN based image processing methods. However, by integrating the blur kernel classification and the deconvolution operation into the proposed image deblurring framework, our method can significantly enhance the deblurring performance for QR barcode. In the future, we would explore to combine the characteristics of QR barcode image while designing the CNN architecture. Meanwhile, the execution time of the proposed method is not applicable to real industrial scenarios, which should be solved through the optimization in the programming platforms and languages.

It is worth notable that adjustment to the architecture of the proposed convolution neural network including the number of convolutional layers and size of the convolution kernel would contribute to improve the accuracy of the blur kernel classification. However, as the accuracy of classification by the currently proposed CNN architecture had achieved at 99.9%. Thus, we did not testify and compare the performance of our proposed CNN architecture with different number of convolutional layers and size of convolutional kernel. However, we believe that there would be performance enhancement through exploiting deeper convolutional neural network structure. In the future, we will continue to carry out corresponding researches.

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References

1. Battiato S (2002) Restoration of out-of-focus images based on circle of confusion estimate. Proceedings of SPIE - The International Society for Optical Engineering 4790(2):408–416
2. Bengio Y, Lamblin P, Popovici D, Larochelle H et al (2007) Greedy layer-wise training of deep networks. Adv Neural Inf Proces Syst 19:153
3. Boulanger-Lewandowski N, Bengio Y, Vincent P (2012) Modeling temporal dependencies in high-dimensional sequences: Application to polyphonic music generation and transcription, arXiv preprint arXiv:1206.6392
4. Chan TF, Wong CK (1998) Total variation blind deconvolution. IEEE Transactions on Image Processing. A Publication of the IEEE Signal Processing Society 7(3):370–375
5. Choksi R, van Gennip Y, Oberman A (2017) Anisotropic total variation regularized l^1-approximation and denoising/deblurring of 2d bar codes. Inverse Prob Imaging 5(3):591–617
6. Chu CH, Yang DN, Pan YL, Chen MS (2011) Stabilization and extraction of 2d barcodes for camera phones. Multimedia Systems 17(2):113–133
7. Collobert R, Weston J, Bottou L, Karlen M, Kavukcuoglu K, Kuksa P (2011) Natural language processing (almost) from scratch. The Journal of Machine Learning Research 12:2493–2537
8. Dahl G, Mohamed A-r, Hinton GE, et al (2010) Phone recognition with the mean-covariance restricted Boltzmann machine, in: Advances in neural information processing systems, pp. 469–477
9. Dahl GE, Yu D, Deng L, Acero A (2012) Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. Audio, Speech, and Language Processing, IEEE Transactions on 20(1):30–42
10. Dan TU, Gan YL, Zong-Qi XU (2007) A real-time deblurring algorithm for the qr barcode images. Computer Engineering & Science 29(3):43–45
11. Deng L, Seltzer ML, Yu D, Acero A, Mohamed A-R, Hinton GE (2010) Binary coding of speech spectrograms using a deep auto-encoder., in: Interspeech, Citeseer, pp. 1692–1695
12. Gennip YV, Athavale P, Gilles J, Choksi R (2015) A regularization approach to blind deblurring and denoising of qr barcodes. IEEE Transactions on Image Processing A Publication of the IEEE Signal Processing Society 24(9): 2864–2873
13. Gregersen E, Code QR (2014) https://www.britannica.com/ technology/QR-Code, [Online; accessed 02-July-2014]
14. Guo D, Liu R, Wang X, Lan F (2013) QR barcode decoding chip and decoding method thereof. US Patent 8,550, 352, 8 October 2013
15. Hinton GE, Osindero S, Teh Y-W (2006) A fast learning algorithm for deep belief nets. Neural Comput 18(7):1527–1554
16. Hsu HH, Chang MH, Yen NY (2012) A health management application with qr code input and rule inference, in: International Conference on Information Security and Intelligence Control, pp. 119–122
17. Jain V, Seung S (2009) Natural image denoising with convolutional networks, in: Ad-vances in Neural Information Processing Systems, pp. 769–776
18. Jalobeanu A, Blancferaud L, Zerubia J (2004) An adaptive gaussian model for satellite image deblurring. IEEE Trans Image Process 13(4):613–621
19. Jia Y, Shelhamer E, Donahue J, Karayev S, Long J, Girshick R, Guadarrama S, Darrell T (2014) Caffe: Convolutional architecture for fast feature embedding, in: Proceedings of the ACM International Conference on Multimedia, ACM,pp. 675–678
20. Karpathy A, Toderici G, Shetty S, Leung T, Sukthankar R, Fei-Fei L (2014) Large-scale video classification with convolutional neural networks, in: Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, pp. 1725–1732

21. Kim YG, Woo E (2016) Consumer acceptance of a quick response (qr) code for the food traceability system: Application of an extended technology acceptance model (tam). Food Res Int 85:266–272
22. Krishnan D, Fergus R (2009) Fast image deconvolution using hyper-laplacian priors. in nips, in: Advances in Neural Information Processing Systems 22: Conference on Neural Information Processing Systems 2009. Proceedings of A Meeting Held 7–10 December 2009, Vancouver, British Columbia, pp. 1033–1041
23. Krishnan D, Tay T, Fergus R (2011) Blind deconvolution using a normalized sparsity measure, in: Computer Vision and Pattern Recognition, pp. 233–240
24. Krishnan D, Bruna J, Fergus R. (2013) Blind Deconvolution with Non-local Sparsity Reweighting. arXiv: 1311.4029
25. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks, in: Advances in neural information processing systems, pp. 1097–1105
26. Kundur D, Hatzinakos D (2002) Blind image deconvolution. IEEE Signal Process Mag 13(3):43–64
27. LeCun Y, Bottou L, Bengio Y, Haffner P (1998) Gradient-based learning applied to document recognition. Proc IEEE 86(11):2278–2324
28. Levin A (2006) Blind motion deblurring using image statistics 841–848
29. Levin A, Weiss Y, Durand F, Freeman WT (2009) Understanding and evaluating blind deconvolution algorithms, in: Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pp. 1964–1971
30. Lin P (2016) Distributed secret sharing approach with cheater prevention based on qrcode. IEEE Transactions on Industrial Informatics 12(1):384–392
31. Liu Y, Yang J, Liu M (2008) Recognition of qr code with mobile phones, in: Control and Decision Conference, 2008, pp. 203–206Ccdc
32. Liu N, Zheng X, Sun H, Tan X (2013) Two-dimensional bar code out-of-focus deblurring via the increment constrained least squares filter. Pattern Recogn Lett 34(2):124–130
33. Long J, Shelhamer E, Darrell T (2015) Fully convolutional networks for semantic segmentation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3431–3440
34. Man M S, Dwivedi A, Sonkar C, Prasad R (2012) A QR Code Based Processing For Dynamic and Transparent Seat Allocation in Indian Railway. International Journal of Computer Science Issues. http://www.ijcsi.org/papers/IJCSI-9-3-1-338-344.pdf
35. Ouaviani P, Bottazzi B, Caselli G (2002) A common image processing framework for 2d barcode reading 2: 652–655
36. Pnevmatikakis EA, Soudry D, Gao Y, Machado TA, Merel J, Pfau D, Reardon T, Mu Y, Lacefield C, Yang W (2016) Simultaneous denoising, deconvolution, and demixing of calcium imaging data. Neuron 89(2):285
37. Prasoon A, Petersen K, Igel C, Lauze F, Dam E, Nielsen M (2013) Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network, in: Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013, Springer, pp. 246–253
38. QR Code (2017) https://www.so.com/s?q=%E4%BA%8C%E7%BB%B4%E7%A0%81%E7%94%9F%E6%88%90%E5%99%A8&psid=0d5464aca3162c02017e34ba8e8bd468&src=pdr_guide_2.30&fr=se7_newtab_new
39. Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition, arXiv preprint arXiv:1409.1556
40. Simonyan K, Vedaldi A, Zisserman A (2013) Deep inside convolutional networks: Visualising image classification models and saliency maps, arXiv preprint arXiv:1312.6034
41. Sixou B, Toma A, Denis L, Peyrin F (2017) Iterative choice of the optimal regularization parameter in tv image deconvolution. Inverse Problems & Imaging 9(4):1171–1191
42. Socher R, Huval B, Bath B, Manning CD, Ng AY (2012) Convolutional-recursive deep learning for 3d object classification, in: Advances in Neural Information Processing Systems, pp. 665–673
43. Sörös G, Semmler S, Humair L, Hilliges O (2015) Fast blur removal for wearable qr code scanners. ACM International Symposium on Wearable Computers. ACM, New York, pp 117–124
44. Stork DG, Gill PR (2014) Reading qr code symbols with an ultra-miniature com-putational diffractive imager, in: Computational Optical Sensing and Imaging
45. Tai YW, Tan P, Brown MS (2011) Richardson-lucy deblurring for scenes under a projective motion path. IEEE Transactions on Pattern Analysis & Machine Intelligence 33(8):1603–1618
46. Tarjan L, Enk I, Tegeltija S, Stankovski S, Ostojic G (2014) A readability analysis for qr code application in a traceability system. Computers & Electronics in Agriculture 109(109):1–11
47. Turaga SC, Murray JF, Jain V, Roth F, Helmstaedter M, Briggman K, Denk W, Seung HS (2010) Convolutional networks can learn to generate affinity graphs for image segmentation. Neural Comput 22(2):511–538
48. Walsh A (2010) Qr codes: Using mobile phones to deliver library instruction and help at the point of need. Journal of Information Literacy 4(1):55–65
49. Weston J, Bengio S, Usunier N (2010) Large scale image annotation: learning to rank with joint word-image embeddings. Mach Learn 81(1):21–35
50. Zbar bar code reader, https://zbar.sourceforge.net

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