Two-Dimensional Barcode Image Super-Resolution Reconstruction Via Sparse Representation

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Abstract. To solve the problem of super-resolution reconstruction in the two-dimensional barcode image, this paper applies the technique of super-resolution reconstruction based on sparse representation into this area. Given the characteristics of the two-dimensional barcode image, this paper presents a new approach which selects the orientation gradient and the gradient texture feature as reconstruction features for recovery. Through analyzing the edge characteristics of this kind of image, it is found that the directional derivatives of it are distinct. Thus the Krisch operator is adopted to get the edge gradient of the image as one feature for reconstruction. Besides, the edge direction texture is regarded as another feature for reconstruction because of the distinct texture directivity of the objective image. Therefore, the geometric information as well as the textural information of the image is taken into consideration for reconstruction. The experimental result shows that the proposed algorithm in this paper can effectively reconstruct the input low-resolution barcode image into the corresponding high-resolution one. What's more, compared with other similar super-resolution algorithms, this proposed algorithm improves the quality of the recovery image to a certain extent.

Introduction

High-resolution image can describe the scene in a more detail way, and it has a wide application in many areas, such as computer vision, medical image diagnosis, and high-resolution images and videos. It is expensive to get high-resolution image through directly improving the resolution of the image forming apparatus. Besides, the traditional crafts constraint the resolution improvement of the imaging device. Thus, improving image resolution through software gradually becomes a hot topic.

The super-resolution reconstruction technology [1] is an economical and effective way to improve the image resolution. From the perspective of image processing, this technology reconstructs a high-resolution image single-frame low resolution image or multi-frame ones. There are two methods at present. One is the reconstruction based multi-frame super resolution method [2], and the other is the learning based single-frame super-resolution method [3]. The reconstruction based method is to assume that the low-resolution image is the operating result of image geometric transformation, blur and down sampling on the original high-resolution image. At first, this method establishes the physical model of the image degradation. Then it retrieves the high-resolution image from multi-frame low resolution images. However, it is difficult to determine the parameters of the degradation model. Learning based approach is a research hotspot in recent years. It learns the relationship between high-resolution images and low-resolution ones, and uses this relationship as a priori knowledge to guide the super-resolution reconstruction. However, an effective method to represent such knowledge is vacant in current learning based super-resolution algorithms. To solve this problem, Yang et al. [4] proposes a learning algorithm based on sparse representation, which well establishes the sparse correlation between high and low resolution images. The image of the two-dimensional barcode [5] is composed of particular geometries which are either white or black

and are presented in a plane according to certain rules. With the arrival of 4G network and the popularity of smart phone, the two-dimensional barcode is injected with new vitality. The two-dimensional barcode provides convenient access to business promotions, web browsing and online payment. Through consulting a large number of relevant literatures, it is found that most of the topics focus on how to improve the coding efficiency and how to quickly identify the barcodes [6]. However, there is little study on how to improve the resolution of the barcode image.

With the widely use of two-dimensional barcode, it is high time to elicit high resolution image of the barcode. Recognition is an important step to obtain the information in a two-dimensional barcode. The image is recognized or not as well as the recognition accuracy is closely related to the clarity of the image. However, it is expensive to get high-resolution image through directly improving the resolution of image device. Besides, the demand of portable type constraints the resolution improvement of image device. So the software is used to preprocess the input image, which is inexpensive as well as makes the access of information in the two-dimensional barcode easier. Based on the demand of high-resolution image of the two-dimensional barcode, this paper applies the super-resolution reconstruction technology based on sparse representation to restoration of this barcode image. Besides, this paper improves this reconstruction technology according to the characteristics of the two-dimensional barcode image, which makes it more suitable for reconstruction.

Image Feature Representation

In a certain scope, the low-resolution image can be regard as a result of down sampling of the corresponding high-resolution one. Therefore, there is some form of association between the low-resolution image and the corresponding high-resolution one. Thus, in order to get a suitable and uniform sparse representation of the low and high resolution images, a good constructed feature transformation (namely T) is needed for dictionary training. The dictionary which is trained in this way will make the reconstruction more accurate. Generally, T is chosen as a certain high-pass filter. Freeman et al. [7] used the Laplace transform to extract the edges information of the low- resolution patches as the feature. Sun et al. [8] used Gaussian derivative filters to extract contours in low resolution patches. These image features mainly make use of the geometry information of the image. But they do not take the texture features and the characteristics of the two-dimensional barcode image into consideration.

According to the characteristics of the barcode image, this paper presents a new feature transformation which is more suitable for resolution. After analysis of the barcode image, it is found that the directional derivative of the image is distinct, especially along the vertical and horizontal direction. Therefore, the Krisch edge detection operator is used to extract one feature of the image. Each 3×3 low-resolution patch is assumed as the format in Fig.1.

$$\begin{matrix} A_0 & A_1 & A_2 \\ A_7 & (i,j) & A_3 \\ A_6 & A_5 & A_4 \end{matrix}$$

Fig.1 image patch

Then the edge gradient magnitude is

$$M(i,j) = \max\{|5S_k - 3T_k|\} \ . \tag{1}$$

In Eq.1, $S_k = A_k + A_{k+1} + A_{k+2}$, $T_k = A_{k+3} + A_{k+4} + ... + A_{k+7}$, $k = 0...7$ **Error! Reference source not found.** and A_n is in Fig.1.

In addition, the low gray patches cross with the high gray ones orderly in the barcode image. Therefore the Krisch operator is used to extract the edge direction as the texture feature, namely the gradient texture feature. The mathematical model is

$$d(i, j) = \{k \mid where\ k\ makes\ abs(5S_k - 3T_k)\ be \max imum\} \ . \tag{2}$$

In Eq.2, k notes the eight directions, whose values are 0,1,…and 7, and which are showed in Fig.2. In Fig.3, $p(i, j)$ nodes the corresponding pixel distribution.

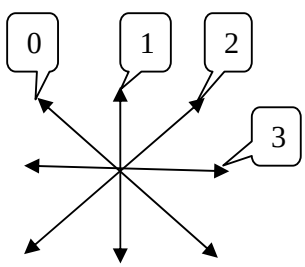


Fig.2 gradient direction

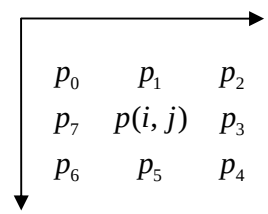


Fig.3 pixel distribution

According to Eq.2, the value range of $d(i, j)$ is from 0 to 7. In order to show the difference between each direction more clearly as well as guarantee the values of direction consistent with the image gray values, Eq.2 is improved to

$$D(i, j) = \{32k \mid where\ k\ makes\ abs(5S_k - 3T_k)\ be \max imum\} . \tag{3}$$

Finally, similar to Yang et al. [4], the second gradients are chosen as the high frequency feature. The two filters for extracting the gradient signals are defined as

$$H_1 = [1, 0, -2, 0, 1],\ \ H_2 = H_1^T \ . \tag{4}$$

Totally four features are produced by Eq.1, Eq.3 and Eq.4. A final and full feature vector V will be produced after concatenating these four features above. That is

$$V = \begin{pmatrix} M \\ D \\ H_1 * IMG \\ H_2 * IMG \end{pmatrix} . \tag{5}$$

In Eq.5, IMG notes the input low-resolution patch. Here, M and D note the results in Eq.1 and Eq.3.

Sparse Representation

The basic idea of sparse representation [9] is assumed that the natural signal can be represented in a compressed way. In other words, the signal is a linear combination of a set of predefined atoms. It is described as

$$x = D\alpha \ . \tag{6}$$

In Eq.6, $x \in R^N$, $D = [D_1, D_2, ..., D_L] \in R^{N \times L} (N < L)$ and $\alpha = [\alpha_1, ..., \alpha_i, ..., \alpha_L]^T \in R^L$. α is the sparse signal and only a finite number of elements in α is not zero. The sparse representation problem can be described as

$$\min \| \alpha \|_0 \text{ , } s.t. \text{ x=D}\alpha \ . \tag{7}$$

In Eq.7, α notes the sparse representation of x. Here, $\| \alpha \|_0$ is the number of non-zero elements in α, D is the sparse dictionary and D_i is the atom of D.

Given the training image patch pairs $\{X^h, X^l\}$, where X^h represents the sampled high-resolution image patches and X^l represents the corresponding low-resolution image ones, the goal is to learn dictionaries for low-resolution and high-resolution patches, so as to the sparse representation of the low-resolution patch is the same as the representation of the corresponding high resolution one [10]. Therefore the training dictionaries of the high and low resolution image are united in

$$\min_{\{D_h, D_l, A\}} \frac{1}{M} \| X^h - D_h A \|_2^2 + \frac{1}{N} \| X^l - D_l A \|_2^2 + \omega \| A \|_1 . \tag{8}$$

In Eq.8, M and N note the dimensions of the high resolution and corresponding low resolution patches in vector form. D_h and D_l note the training dictionary of the high and low resolution image. A notes the sparse matrix.

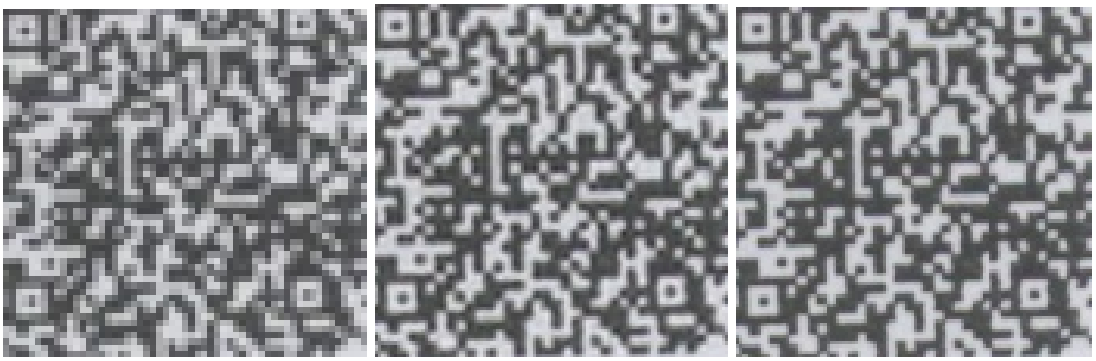
Experiment

This section shows the restoration results of our algorithm and shows the comparison of restoration effects between our algorithm and other algorithms. 10,000 high-resolution and low-

resolution patch pairs were selected randomly from the set of training images. Each 5×5 patch of the input low-resolution image is dispatched orderly, which is taken starting from the upper-left corner with 4 pixel overlap in each direction. To find the balance between the computational efficiency and the quality of the result, the size of the sparse dictionary is chosen as 512.

In this paper, the processed images are selected randomly. In order to explain the problem more clearly, the typical part of an image has been shown. Fig.4 shows the reconstruction results by using the proposed algorithm. Compared with the input low-resolution image, the edges of the restored image is clearer and the overall visual effect of the restored image has been significantly improved. Besides, the restored image is almost as good as the original high-resolution image on the image quality.

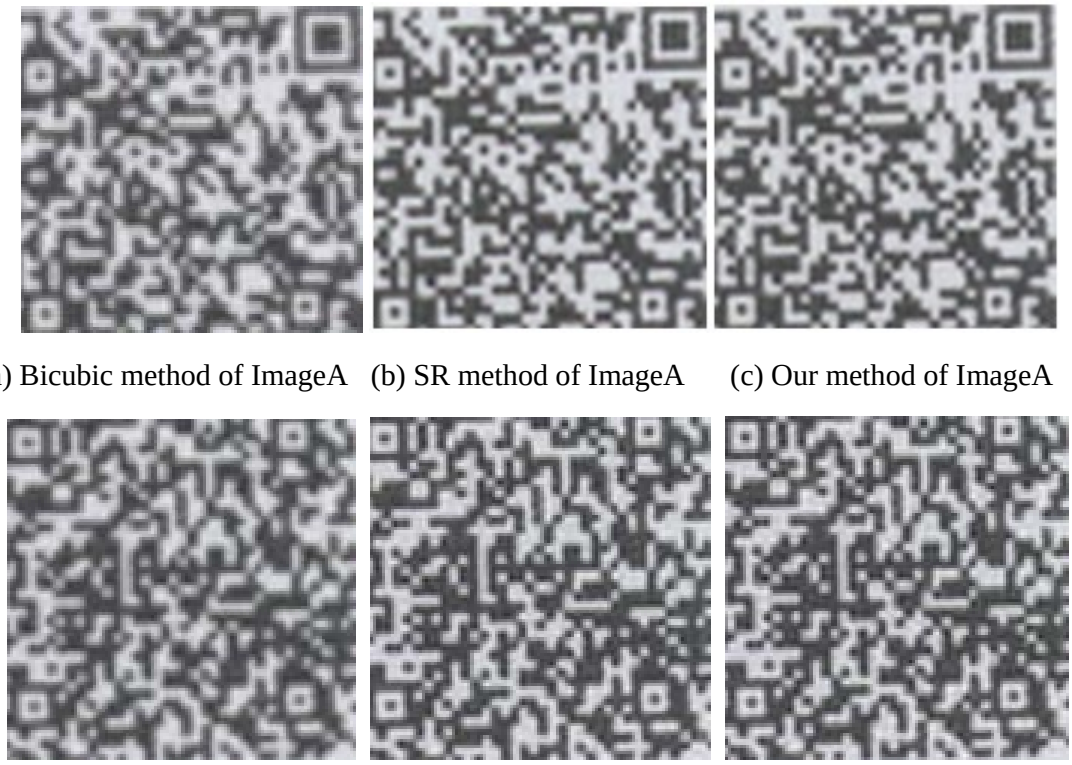
(a) the input of ImageA (b) the restored of ImageA (c) the original of ImageA



(d) the input of ImageB (e) the restored of ImageB (f) the original of ImageB

Fig.4 Results of the barcode images by a factor of 2

Fig.5 shows the recovery result of each method. The Bicubic method [11] produces a negative smooth effect. The SR method [4] produces some negative ringing effect. Our method has a better reconstruction and has gotten a clearer image. Table 1 shows the PSNR of each method. Our method gets a better PSNR.



(a) Bicubic method of ImageA (b) SR method of ImageA (c) Our method of ImageA

(d) Bicubic method of ImageB (e) SR method of ImageB (f) Our method of ImageB

Fig.5 recovery result of each method

Table 1 the PSNR of each method

Image	Bicubic	SR	Our method
ImageA	31.184[dB]	32.479[dB]	**33.037[dB]**
ImageB	29.096[dB]	28.553[dB]	**29.226[dB]**
ImageC	21.933[dB]	22.835[dB]	**22.917[dB]**
ImageD	26.483[dB]	27.475[dB]	**27.873[dB]**
ImageE	28.609[dB]	29.046[dB]	**29.592[dB]**

Summary

This paper applies the technique of super-resolution reconstruction based on sparse representation to the reconstruction for the two-dimensional barcode image. And given the characteristics of the two-dimensional barcode image, this paper presents a new approach which selects orientation gradient and gradient texture features as image reconstruction features for recovery. Experiment results demonstrate that the proposed algorithm can effectively reconstruct the input low-resolution barcode image into the corresponding high-resolution one. However, one of the most important questions for future investigation is to determine the optimal correlations among these features for the reconstruction tasks.

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