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Influence of Training Set and Iterative Back Projection on Example-based Super-resolution

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***Abstract*— Example-based super-resolution has become increasingly popular over the last few years for its ability to defeat the restriction of classical multi-frame approach. In this paper we present the influence of training set on example based method. A difficulty with example-based methods is that they require storing and searching large databases. Additionally, it is not guaranteed that the database contains the true high-resolution details which may cause "illusion" effect. Furthermore, this database requires being large enough to prepare good results which make learning or searching computationally more requesting. The contribution of this paper involves the two following areas: different method of generating training set from training images and different structure of training patches. Additionally, we apply Iterative back projection as a post-processing technique. It can be seen from the experimental result that increasing the number of the training set doesn't have much significant influence on PSNR and MSE. Also, it can be seen when the training set contains high resolution image or part of it, PSNR increases 2.7db and the MSE decreases 2.8. By using Iterative back projection, PSNR increases 0.8db and MSE decreases 0.65 compared to proposed algorithm in [8] and also improves visual quality of enlarged images.**

Keywords-super-resolution; example-based; iterative back projection.

I. INTRODUCTION

Super-resolution (SR) performs an important role in image processing applications because of the massive amount of low resolution video and image material. Super resolution image reconstruction is a promising technique of digital imaging which attempts to generate a raster image with a higher resolution than its source.

The super-resolution technology can be categorized as the single image super-resolution and the multiple images super-resolution. This paper concentrate on single-frame super-resolution i.e. the source is a single raster image. In almost 30 years, many tries have been made to gain a high-resolution image [1]–[20]. Single image super resolution approaches can be divided into three categories the interpolation method, the super-resolution reconstruction method and the learning-based super-resolution method.

The interpolation approach is the most intuitive technique for the image super-resolution. The most typical interpolation algorithms include the nearest neighbor, Bicubic and bilinear. These methods are fast and easy algorithm, thus assuring the real-time demand in general, but these can't demonstrate beneficial extra high-frequency information. The reconstruction-based super-resolution method has been progressed gradually. The Iterative back-projection (IBP) proposed by Irani and Peleg (1991) is a typical method in the reconstruction of the super-resolution image. The IBP is a reconstruction-based method with low computational complication that can be used in real time applications but it often generates many artifacts along the strong edges. Another class of super-resolution methods is learning based approaches. This methods use a learned co-occurrence prior to predict the correspondence between low-resolution and high resolution image patches. It's difficult to reconstruct the super resolution image by increasing the number of the low-resolution images to generate new high-frequency details. Under this content, the priori knowledge concerning the images themselves seems very important. Because of this, the learning-based super-resolution technology appears as an active research area.

In this paper, we explore the influence of the training set on example-based method and apply Iterative back projection on the high resolution image obtained by example-based algorithm. This IBP method can minimize the error significantly by back projecting the error iteratively.

In Section II, we give a review of the related example-based algorithm for super-resolution and the IBP algorithm. In section III, we discuss how dataset changes will influence the output high resolution image and present Iterative back projection as a post processing step for example-based super-resolution. Section IV presents experimental results and analysis. Finally, section V concludes this work.

II. REVIEW OF IBP ALGORITHM AND EXAMPLE BASED RECONSTRUCTION FOR SUPER-RESOLUTION

A. *Exampled-based Method*

Our stimulant comes from exampled-based method Freeman et al (2002) [8] propose an example-based super-resolution method. The method includes two steps: learning and a reconstruction step. Firstly, the high-resolution images form the dataset, which possess the high-frequency of the images and subsample low-resolution images. Later on, every patches of the low-resolution image searches the best relevant pairs from the dataset to reconstruct the high resolution image by combining the high-frequency information to the low-resolution image. In this method, extra high-frequency information can be obtained.

To obtain the dataset proposed by Freeman et al., the first step is to decay the high-resolution image following the degradation model so as to for the training set. The high-resolution image is blurred and subsampled to obtain the low-resolution image. The low frequency of the high-resolution image can be obtained by zooming this low-resolution image. And the high-frequency of the high-resolution image is the differences between the zoomed low-resolution image and the true high-resolution image. Finally, the low- and high-frequency are both broke into patches in the same certain size. Each low- and high-frequency patch which are in the same position are generated a training patch.

Our work is based on [8] which builds dataset for the super-resolution algorithm from band-pass and high-pass pairs and store the high-resolution patch corresponding to every possible low-resolution image patch, these patches are M × M low-frequency and N × N high-frequency patches. In [8] patch pairs normalize by the average absolute value of the low-frequency patch (add a small ε). The pixels in the low-frequency patch and the high frequency overlap are concatenated to form a search vector. The dataset is stored as a set of such vectors, so we search for a match by finding the nearest neighbor in the training set. A user-controlled weighting factor α adjusts the relative importance of matching the low frequency patch versus matching the neighboring high-frequency patches in the overlap regions (1). After finding a match, reverse the contrast normalization on the high frequency patch and add it to the initial interpolation to obtain the output image (see Fig. 1). Finally, these high-resolution patches reconstruct an output high-resolution image still in raster scan order [8].

$$\alpha = 0.1\frac{M^2}{2N-1} \tag{1}$$

B. *Enforcing Reconstruction Method*

The Iterative back-projection (IBP) is a classical super-resolution method with low computational complexity that can be applied in real time applications. It back projects the error and also back-project the high frequency. This approach of SR is fast and robust to noise with edge perseveration. The procedure can be summarized as mathematical equation by following two steps iteratively [22], [23]:

1) Compute the error from LR images as (2).

$$X_e = (y - y^{(n)}) \uparrow S \tag{2}$$

Where, $\uparrow S$ is up-sampling; y is initial input LR image; $y^{(n)}$ is simulated LR image of n^{th} iteration; X_e is error estimation. Estimation of the simulated LR image is given as (3).

$$y^{(n)} = (X^{(n)} * W) \downarrow S \tag{3}$$

Where, $\downarrow S$ is down-sampling; $y^{(n)}$ is simulated LR image of n^{th} iteration; W is degradation function; $X^{(n)}$ is estimated HR image of n^{th} iteration.

2) Update the HR image by back-projecting the error X_e, as (4).

$$X^{(n+1)} = X^{(n)} + X_e + HPF(X^{(0)}) \tag{4}$$

III. INFLUENCE OF TRAINING SET AND ITERATIVE BACK PROJECTION ON EXAMPLE-BASED SUPER RESOLUTION

In the section, first, we describe the effect of the training set on exampled-based method. We show that when the training images are highly relevant to the input image - the high relation in here means that the input image and the training image both describe the similar stuff -very good effects can be obtained with a few training images, which means the output high-resolution image is quite similar to the actual image. When the training images and the input image are poorly relevant, large training images are needed to get a good effect. Therefore, the example-based method is sensitive to the selection of the training image. In the following paper we show the experimental result.

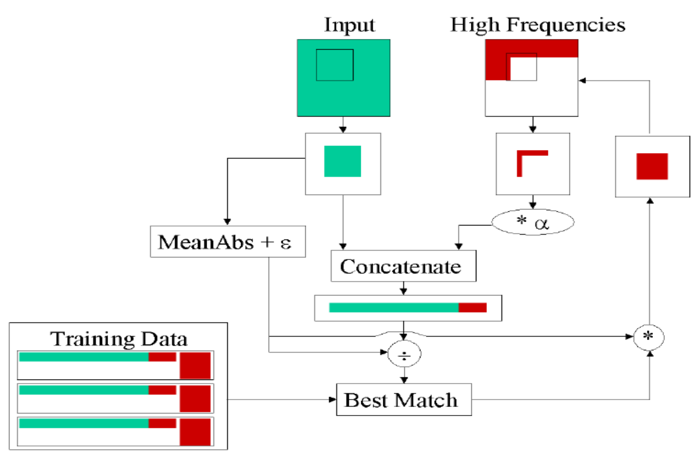

Figure 1.Block diagram showing raster-order per-patch processing. At each step, local low- and high-frequency details (shown in green and red, respectively) are used to search training set for a new high-frequency patch, which is added to the high-frequency image [8].

The high-resolution image produced by the exampled-based approach of the previous section may not satisfy the reconstruction constraint exactly. We eliminate this discrepancy by adding back projection method as a post processing step for filtering image to improve performance of example based method by emphasizing pixels having significant change in local intensity.

We consider the image $X^{(0)}$ as the initial high-resolution image produced by the exampled-based approach and the image y as the original low resolution image. The task is to reconstruct the HR image from the observed LR image. An estimated high frequency image $X^{(n)}$ should produce the same LR image y if passing it through the same image formation process as (3).

So, in the iteration process, the reconstruction error X_e is calculated as (2) and back projected to the estimated HR image to compensate the high frequency error as (4). The iteration process reduces the blurring effect. The block diagram of proposed algorithm is shown in Fig. 2.

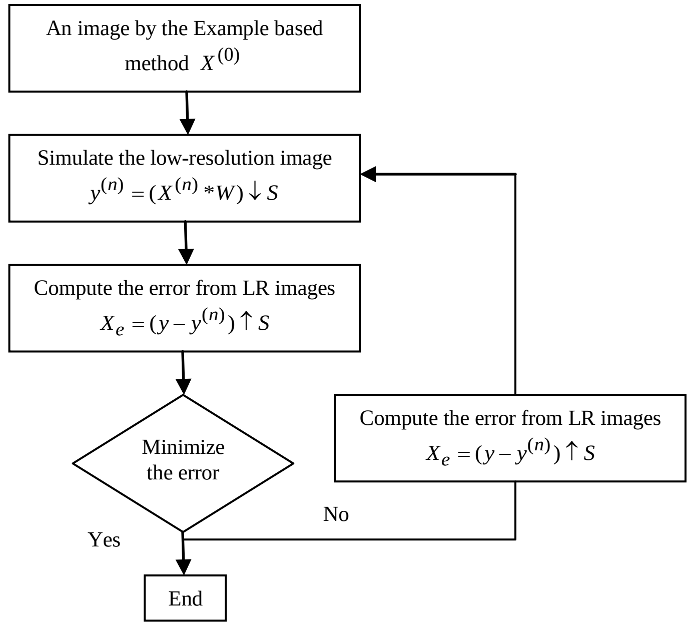

Figure 2.The process of proposed algorithm

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we perform experiments by nine test images (shown in Fig. 3) to demonstrate the efficacy of the proposed method and the influence of selection of images and size of patches. Additionally, the Bicubic interpolator, Freeman's method, and our proposed method are used for comparison.

This work based on [8] which uses 5 × 5 pixel high-resolution patches (N= 5) with 7 × 7 pixel low-resolution patches (M = 7). The overlap between adjacent high-resolution patches was 1 pixel. These patch sizes capture small details well.

We employ the PSNR (Peak Signal-to-Noise Ratio) and MSE (Root Mean Square Error) as the evaluation metrics. As we know, sometimes the value of PSNR is opposite of our feeling. We let the PSNR and RMSE as a reference based on our feeling.

A. Influence of training images selection on the experimental result

It can be seen from the Fig. 4 and Table I that when the training images are more relevant to the input image very good effects can be obtained with few training images. The result obtained for three testing images shows better image quality by decreasing MSE and increasing PSNR for High Relevance than Low Relevance.

Moreover, the result obtained with part of the true high resolution image has better image quality by decreases MSE and increases PSNR than Cubic interpolation. Therefore, the example-based method is sensitive to the selection of the training image. We adjust the size of the patch on 7×7 in low-resolution and 5×5 in high-resolution with 3 training images.

Figure 3.Test images we use in our experiments: Parrots, plants, Starfish, Lena, Flower, Butterfly, bike, Hat, Leaves.

B. Influence of the number of training sets on the experimental result

The experimental results acquire from the training sets containing the images of different number. It can be seen of the results (see Table II, Table III, Fig. 5 and Fig. 6) that the increase of training image number leads to higher quality of the reconstructed image when the training image is less relevant to the input image; however, when the more relevant training image is, the quality of the reconstructed image rises at a lower speed. We adjust the size of the patch on 7*7 in low-resolution and 5*5 in high-resolution and repeat the examination for two conditions, when the training image isn't highly related to the input image and when the training image is highly related to the input image.

C. Influence of the patches size on the experimental result

The experimental results obtained from patches of different sizes and for the training set with 9 images are shown in Table IV and Fig. 7. If the size of the patch is too small, the training set is enlarged and more patches of the input image would be calculated, if the patch is too large in size, the matching error is magnified and the acquired high-resolution image is low in quality. We adjust the training set for 3 training images when training images are highly related to the input image.

D. Influence of the Enforcing Reconstruction Method

The results obtained by adding the Iterative back projection as a post processing step for different types of images show improvements over other approaches in terms of PSNR and MSE value as we mentioned previously (see Table V and Fig. 8). We adjust the training set for 3 training images when training images are highly related to the input image with the size of the patch on 7*7 in low-resolution and 5*5 in high-resolution.

TABLE I. PSNR AND MSE COMPARISION FOR DIFFERENT TRAINING IMAGES

	Low Relevance	**High Relevance**	**Bicubic**	**With part of true HR image**
PSNR(db)	27.664	30.377	27.875	27.902
MSE	10.551	7.720	10.298	10.254

Figure 4.The images from the left to right include: Top row: input low-resolution image; the original high-resolution image; the high-resolution image obtained when the training images are highly related to the input image. Bottom row: the high-resolution image obtained when the training images aren't highly related to the input image; the high-resolution image obtained with part of the true high resolution image; Bicubic.

TABLE II. PSNR AND MSE COMPARISION FOR DIFFERENT NUMBER OF TRAINING IMAGES WHEN THE TRAINIG IMAGES AREN'T HIGHLY RELATED TO THE INPUT IMAGE

	Number of training images	
	3	***8***
PSNR(db)	27.6649	27.8888
MSE	10.5510	10.2826

Figure5.The images from the left to right when the training images aren't highly related to the input image include: the high-resolution image obtained for 3 training images; the high-resolution image obtained for 8 training images.

TABLE III. PSNR AND MSE COMPARISION FOR DIFFERENT NUMBER OF TRAINING IMAGES WHEN THE TRAINIG IMAGES ARE HIGHLY RELATED TO THE INPUT IMAGE

	Number of training images	
	3	***8***
PSNR (db)	30.3775	30.3778
MSE	7.7216	7.7206

Figure 6.The images from the left to right include when the training images are highly related to the input image: the high-resolution image obtained for 3 training images; the high-resolution image obtained for 8 training images.

TABLE IV. PSNR AND MSE COMPARISION FOR DIFFERENT PATCH SIZE OF TRAINING IMAGES WHEN TRAINING IMAGES ARE HIGHLY RELATED TO THE INPUT

TABLE V.

	LR patches size 5*5, HR patches size 3*3	**LR patches size 7*7, HR patches size 5*5**	**LR patches size 9*9, HR patches size 7*7**
PSNR(db)	30.1010	30.3775	29.4827
MSE	7.9706	7.7216	8.6279

Figure 7.The result of LR patches size 5*5, HR patches size 3*3; the result of LR patches size7*7, HR patches size 5*5the result of LR patches size 9*9, HR patches size 7*7.

TABLE VI. PSNR AND MSE COMPARISION FOR DIFFERENT METHODS

	Method in [8]	**Our method**	**Bicubic**
PSNR(db)	30.3778	31.1401	27.8751
MSE	7.7206	7.0719	10.2988

Figure 8.The images from the left to right include: Freeman et al, our method, Bicubic interpolation.

V. CONCLUSIN

Based on example-based image super-resolution, the contributions of our work are two-fold. First, this paper has made the experiment in respect to training image selection, training image number, size of the patches of training images, and secondly, we present an example-based image super resolution algorithm based on Iterative back projection method to improve the experimental results. The experiment proves that the proposed method obtains better results by increasing PSNR about 0.8db and decreasing MSE about 0.65 compared to proposed algorithm in [8]. Also, it can be seen that increasing the number of training set doesn't have much significant influence but when training set contains high resolution image or part of it, PSNR increases 2.7db and the MSE decreases 2.8 compared to when the training images aren't highly related to the input image.

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