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Super-Resolution of an Image using Examplar Technique

Sandip S.Gujare[1], Sudhir S.Kanade[2]

PG Student, Department of Electronics and Telecommunication Engineering TPCT's College of Engineering, Osmanabad, (M.S.), India[1]

Professor and Head, Department of Electronics and Telecommunication Engineering, TPCT's College of Engineering, Osmanabad (M.S.) India[2]

ABSTRACT: Due to the limitation of the producing technique and value of the image sensing element and optics, it's expensive or troublesome to get the high-resolution image. under this situation, it's necessary to use the super-resolution technology to boost the quality of the image, so as to induce more data and details. as a result of the needing of some areas, like public safety, military, becomes higher and better for the image resolution, the super-resolution technology is of nice theoretical and practical meaning. In light of the number of the initial low-resolution images, the super-resolution technology may be classified because the single image super-resolution and therefore the multiple images super-resolution. For the single image super-resolution, this paper conducts the subsequent tasks. Stressing on finding out the example-based super-resolution methodology. This methodology primarily applies the Markov Network to model the spatial relationships between low-resolution image patches as well as the corresponding high-resolution image patches. in this manner, the comparatively ideal results are obtained.

KEYWORDS : Super resolution, High resolution, Low resolution,Example based.

I. INTRODUCTION

Super-resolution (SR) performs a crucial role in image processing applications as a result of the large quantity of low resolution video and image material. Super resolution image reconstruction may be a promising technique of digital imaging that makes an attempt to get a raster image with a higher resolution than its source. Freeman et al. [1] proposed the thought of example-based super-resolution algorithm. Firstly, the high resolution images are applied to create the training set , that contains the high-frequency of the images and a group of subsample low-resolution images. Later on, within the training set, the information regarding the high-frequency and therefore the corresponding low-frequency is learnt. Then, this information is employed to predict the details of other low-resolution images. The overview of their method as shown in the Figure 1 [1]

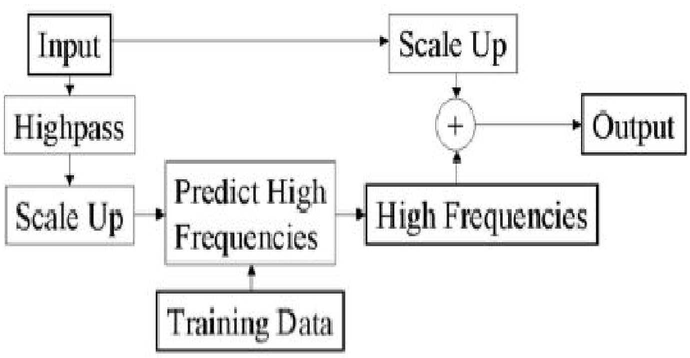

Fig. 1. Freeman's method

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II. PROPOSED SCHEME

Recently, the example-based super-resolution technique has been extensively studied as a result of its vivid perception. However, this type of technique directly transfers the high-frequency details of the examples to the low-resolution image, acquisition false structures and over-sharpness around the texture regions. in this paper, the study relies on example based technique of super resolution. Fig.2 shows the summary of projected technique.

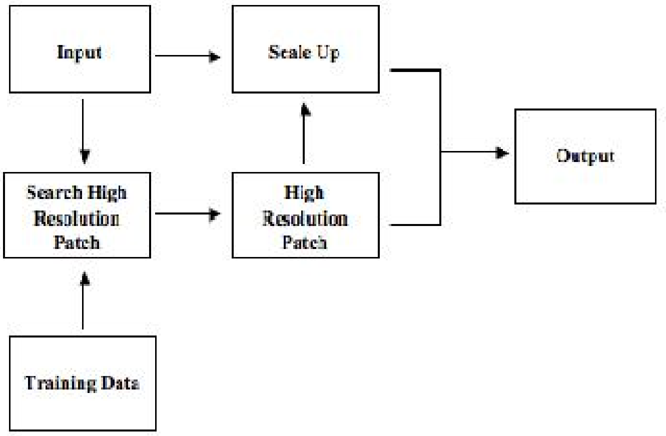

Fig. 2. The outline of our proposed method

A. Training set generation

To generate our training set, we tend to begin from a group of high-resolution pictures and degrade every of them in an exceedingly manner similar to the degradation we tend to commit to undo within the images we tend to later process. Typically, we tend to blur and subsample them to form a low-resolution image of one-half the number of original pixels in every dimension. to vary resolution by higher factors, we tend to usually use the only octave algorithm recursively. We apply an initial analytic interpolation, like cube like spline, to the low-resolution image. This generates an image of the specified range of pixels that lacks high-resolution detail. In our training set, we tend to solely ought to store the variations between the image's cubic- spline interpolation and also the original high-resolution image. Fig. 3 (a) and 3(c) show low- and high-resolution versions of an image. Fig. 3(b) is that the initial interpolation .We wants to store the high-resolution patch corresponding to each possible low-resolution image patch these patches are usually 5 × 5 and 7 × 7 pixels, respectively. Even proscribing ourselves to plausible image information, this can be a large quantity of information to store, therefore we tend to should preprocess the images to get rid of variability and build the training sets as usually applicable as possible. we tend to believe that the very best spatial-frequency components of the low-resolution image fig. 3(b) are most significant in predicting the additional details in Fig. 3 (c).we tend to filtrate the lowest frequency components in Fig. 3(b) in order that we tend to don't have to store example patches for all possible lowest frequency component values.

We additionally believe that the relationship between high- and low-resolution image patches is actually independent of local image contrast. We tend to don't need to have to store examples of that underlying relationship for all possible values of the local image contrast. Therefore, we tend to apply a local contrast normalization that we tend to describe shortly within the "Prediction" section. In Fig. 3(d) and 3(e), we tend to use the resulting band pass filtered and contrast normalized image pairs for training. We tend to undo the contrast normalization step after we reconstruct the high-resolution image.

In our proposed technique, however, we tend to directly produce the training patches from the training images in a certain size that's the results of the scale of the low-resolution patch increased by the magnification times. During this method, the dimension of the training patches is reduced mostly, as a result of the training patches of

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Freeman's methodology is formed from pairs of low- and high-frequency while we tend to simply store verity size of training patches, the dimension is half the Freeman's in the same size of high-resolution patches.

In the same time, Candès and Recht [2] have proved that, by evenly extracting k elements from a matrix $M \in R^{m \times n}$ whose rank is r, it's probable to restore this matrix. This means we can approximately restore the true high-resolution image by low-resolution patches. Assuming the low-resolution patch is sized $i * j$, so the number of the pixels of the patch is $k = i * j$. Through $L_2 - norm$, the best matching high-resolution $m * n$ patch which is close to the patch is $k = i * j$. Through $L_2 - norm$, the best matching high-resolution $m * n$ patch which is close to the true high-resolution image according the theory from Candès and Recht [2] is matched by comparing k pixels Fig. 4., where $m = i * s$ and $n = j * s$. (s - magnification times).

We seek for matches using an L2 norm. Because of the high dimension of the search space, finding absolutely the best match would be computationally preventive. Instead, we tend to use the tree-based, approximate nearest neighbor search. The tree is made by recursively splitting the training set within the direction of higher variation. At every step, we tend to divide the set of tiles in half to maintain a balanced tree. We tend to use a best-first tree search to search out a good match. This enables for a speed quality trade-off: by searching more tree branches, we will find a much better match. As a result of best-first search is unlikely to offer the true best match without searching most or all of the tree. This improves the match with negligible cost. Altogether one-pass algorithm examples in this article, we tend to connect every patch pair to its 32 approximate nearest neighbors, that we tend to calculate with a technique almost like Nene and Nayar.[3]

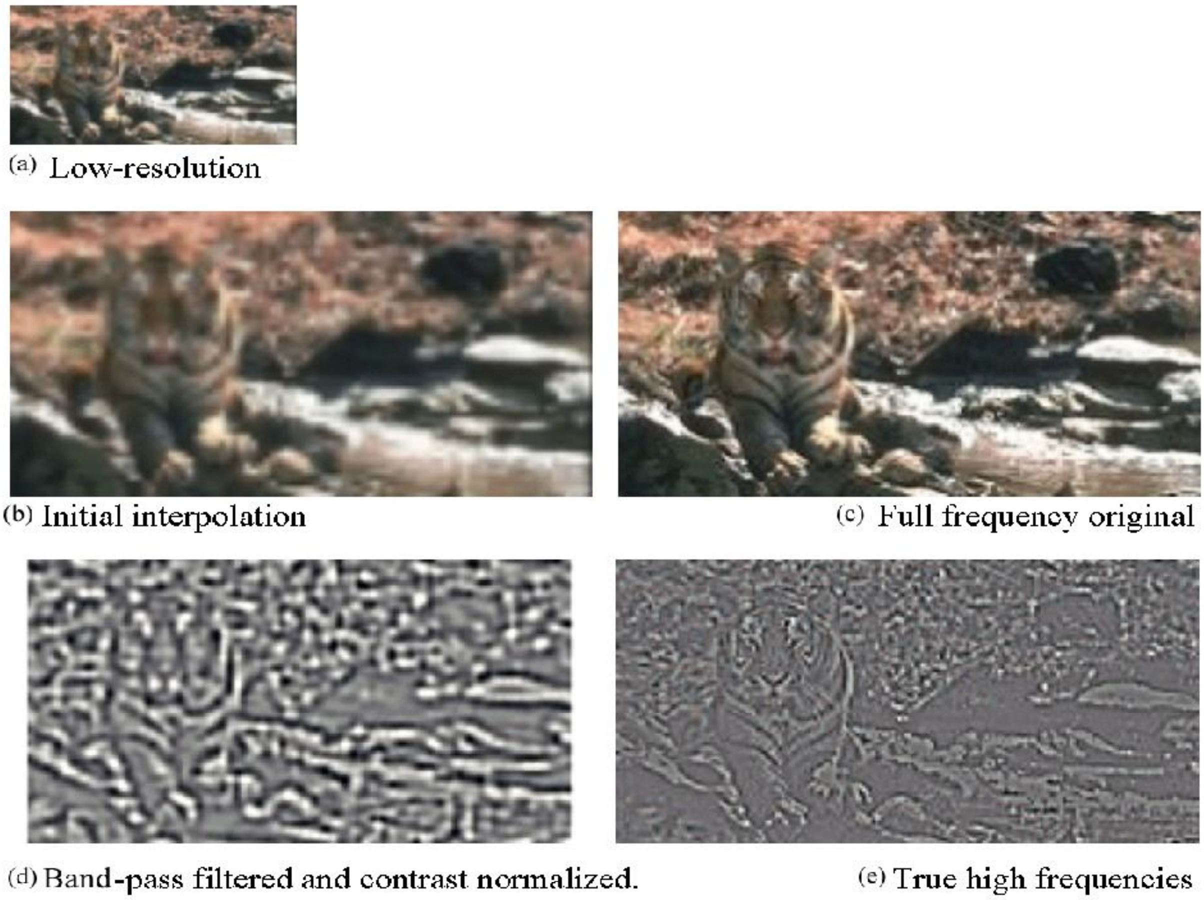

Fig. 3. Preprocessing steps for training images. (a) low-resolution image (c) corresponding high-resolution image. (b) Intial Interpolation (d) Bandpass filtered and contrast normalized (e) True high frequencies image

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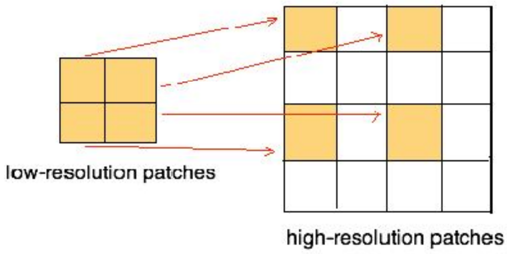

Fig. 4.The match method between low- and high-resolution patches

A. Searching

For a low-resolution patch, it's necessary to inquire a training set containing many thousands patches. If the most effective matching patch is acquired by a brute force technique, the computation value is large. Here, we tend to use the k-d tree to seek the closest neighbor. The k-d tree is a binary space partitioning tree structure made for organizing points in a k-dimension space [4]. During this structure, every non-leaf node will be thought of as implicitly half-spaces that the space is split into two parts by a splitting hyper plane. And therefore the every half-space will be divided recursively within the same method all the half-space area unit divided into the left and right sub tree. The division of the k-d tree is conducted on the axis, and every one the hyper planes area unit perpendicular to the corresponding axis as an example, if the division is conducted on the axis x, the hyper plane will be determined by the given worth of x, since the direction of the normal vector of the hyper plane is on the axial direction of x. The hyper plane divides the first space into two new subspaces. As for all the points within the left space, their x values area unit lower compared with points within the right space. The k-d tree may be a fairly effective organization structure for the k-dimension knowledge. It's a specific advantage within the search field regarding the high-dimension space, such as the k nearest neighborhood search. Therefore, the k-d tree will be applied within the high-dimension space-searching algorithm of the patch.

B. Matching

Freeman et al.[1] purpose the missing high-resolution details can't be predicted with solely the local information alone , as a result of if we tend to pre-process an input low-resolution image then break it in to several patches and search the missing high-frequency details, we'll notice the searched high-frequency patches quite totally different see the subsequent Fig. 5. This shows the local patch information isn't enough to predict the detailed information of the high-resolution , however the result of the spatial neighborhood ought to be taken under consideration. In our technique , throughout the method of breaking the low-frequency image by raster scan order, each patch should be part overlapped by its neighbor to keep the accordance of the space neighborhood Fig. 6.

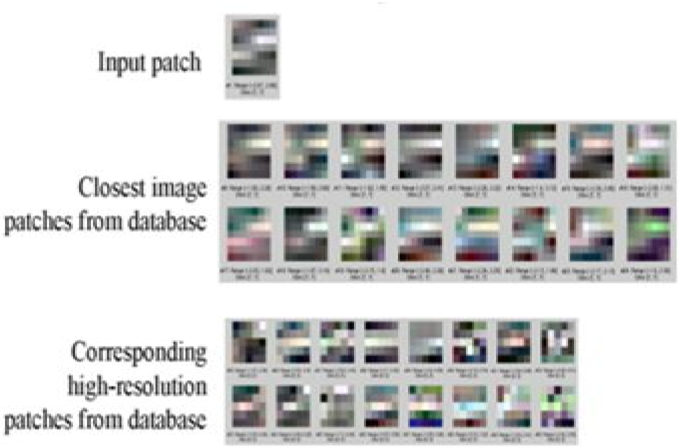

Fig. 5. Input patch, and low-resolution patch (center rows) and corresponding high- resolution (bottom rows) patches.

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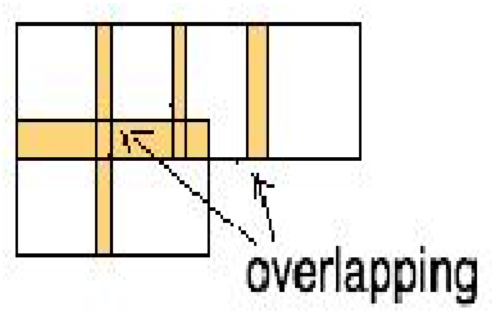
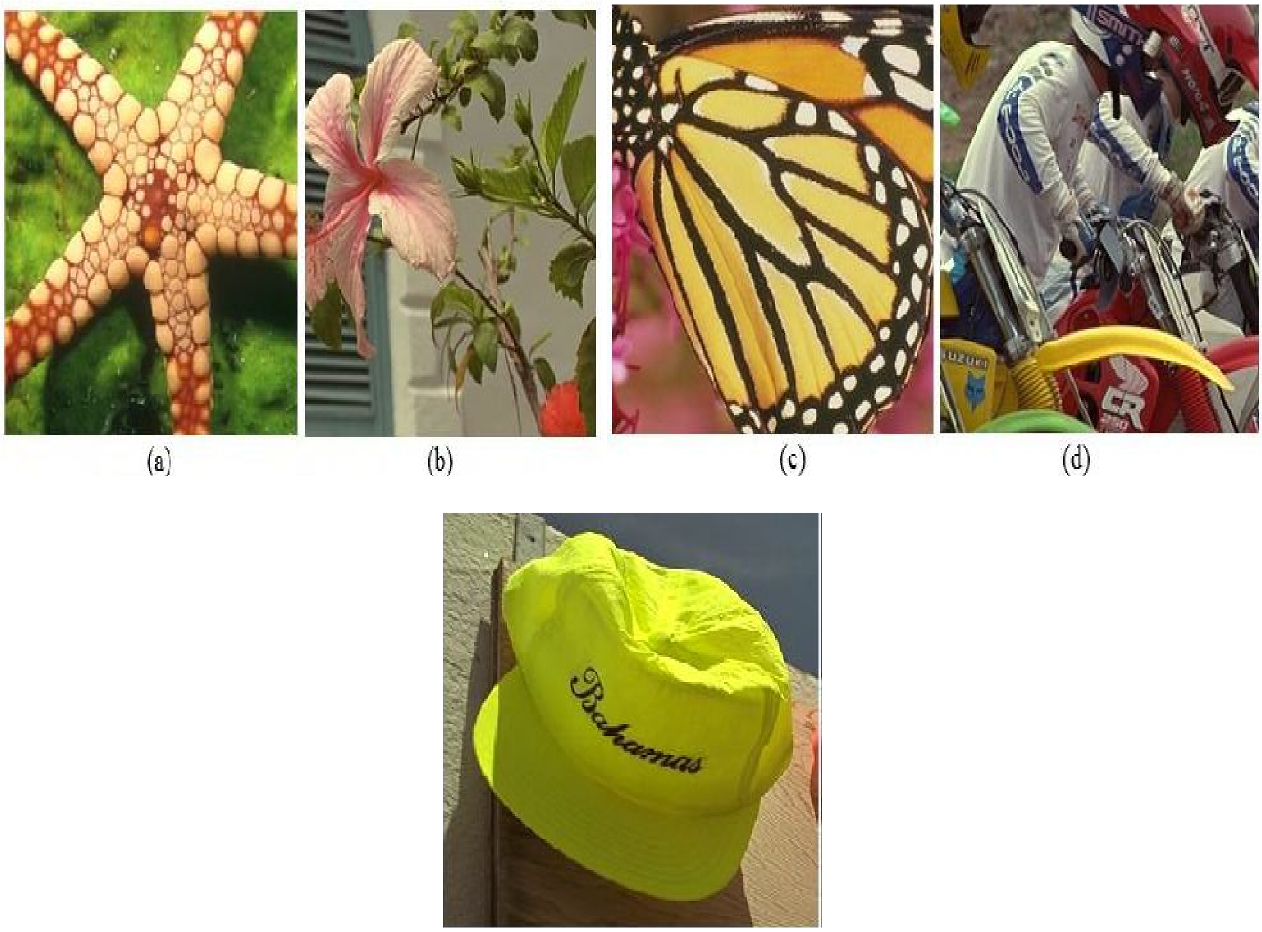


Fig. 6. Break the image into patches

III. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we perform experiments by five standard test images shown in Fig. 7. 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 [1] which uses 5 × 5 pixel high-resolution patches with 7 × 7 pixel low-resolution patches .The overlap between nearby high-resolution patches was pixel. These patch sizes get details. We employ the PSNR as the evaluation metrics.



(a) (b) (c) (d)

(e)

Fig. 7. Test images used in experiments: (a) Starfish, (b) Flower, (c) Butterfly, (d) Bike, (e) Hat

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Image	Bicubic Interpolation	Chang's method [5]	Our approach
Starfish	25.6129	28.3736	31.7973
Flower	26.1858	28.5701	31.3774
Butterfly	22.7827	25.8291	29.1353
Bike	21.9979	24.1312	26.8564
Hat	28.3100	26.3727	30.2991

TABLE I. PSNR(db) comparison

A. The influence of training image selection on the experimental result

It can be seen from the fig. 8. and Table II that when the training image is very relevant to the input image the high relation in here implies that the input image and therefore the training image both describe the similar stuff excellent effects can be obtained with a few training pictures, which implies the output high-resolution image is kind of almost like the actual image. Once the training and therefore the input image area unit poorly relevant, a large training image is required to induce a good effect. Therefore, the example-based method is sensitive to the selection of the training image.

Fig. 8. The images from the left to right : 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.

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	High Relevance	Low Relevance
PSNR(db)	27.82	27.55

TABLE II: The PSNR of the high relevance and low relevance

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

The experimental results acquired from the training sets containing the images of different number as in fig. 9. It are often seen experiment that the rise of training image number ends up in higher quality of their constructed image; but, when the high relevant coaching image is out numbered 50, the quality of there constructed image rises at a lower speed.

Fig. 9.The high-resolution image obtained for 3 training images; the high-resolution image obtained for 8 training images

C. Influence of the patch size on the experimental result

In the training set that there are 250 images, the experimental results obtained from patches of various sizes are shown in Table III. If the size of the patch is simply too small, the training set is enlarged and a lot of patches of the input image would be calculated; if the patch is simply too large in size, the matching error is enlarged and therefore the acquired high-resolution image is low in quality.

	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)	30.1011	30.3773	29.4826

TABLE III: The PSNR of the different patch sizes

D. Comparison between Freeman's algorithm and our method

Under the same training images, we tend to compare the best images (the size of the patch is 5*5 in low resolution and 7*7 in high-resolution) made in Freeman's method and those in our method (the size of the patch is 3*3 in low-resolution and 6*6 in high-resolution) see the subsequent fig. 10.

a   Freeman's method b   Our method c

Fig. 10. a) the LR input image; b) the result of Freeman's method; c) the result of our proposed method.

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The following Table IV lists the comparison between the original image and the output image PSNR obtained by Freeman's method and the propose method respectively. We can discover that the proposed method is better.

	Freeman's Method [1]	**Our proposed Method**
PSNR(db)	15.45	21.89

TABLE IV. The comparison between PSNR obtained by freeman's method and the propose method respectively

IV. CONCLUSION

Based on the image super-resolution restoring technology, this paper has unrolled a primary study, with the follows jobs being completed:

1. Comparison and analyzing the thought super-resolution algorithms based on specifically analyzing the principle of high-resolution restoration.
2. Improving the super-resolution technology based on the exemplar. we've created the experiment within the respects of training image selection, training image number, size of the patches of training images, so compared the our method with the example-based technique. The experiment proves that our method obtains higher results.

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