SINGLE IMAGE SUPER RESOLUTION: A COMPARATIVE STUDY

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ABSTRACT

The majority of applications requiring high resolution images to derive and analyze data accurately and easily. Image super resolution is playing an effective role in those applications. Image super resolution is the process of producing high resolution image from low resolution image. In this paper, we study various image super resolution techniques with respect to the quality of results and processing time. This comparative study introduces a comparison between four algorithms of single image super-resolution. For fair comparison, the compared algorithms are tested on the same dataset and same platform to show the major advantages of one over the others.

KEYWORDS

Super resolution, Interpolation, Neighbour filling, Resizing, Low resolution

1. INTRODUCTION

Supper resolution (SR) is the process of enhancement the resolution of images. Resolution is a measure of frequency content in an image. There are always requests for good quality images from low one, although the cameras for high resolution (HR) images are expensive. Also image capturing setting is not ideal so the resulting images are blurred and noisy. Regarding that using of supper resolution techniques to enhance resolution of images and maintain the details of them is preferable [1-4].

HR images are frequently used in large applications such as satellite imaging, sports images, medical imaging, computer vision, remote sensing, surveillance systems, object detection and recognition. The need of zooming of images to analyze visual information also increases the request for super-resolution [5-7].

In general, super resolution techniques are divided into two categories, which are multi image super-resolution and single image super-resolution [2]. Multi image super-resolution is the process of generation high resolution image from multiple low resolution images. Single image super-resolution is the process of generating high-resolution image from its low resolution image [8]. This study focuses on single image super-resolution techniques.

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Many researchers have developed algorithms for solving super resolution issues. These algorithms could be classified into three types: interpolation-based, learning-based and reconstruction-based [9-10]. Interpolation based algorithms such as nearest neighbour interpolation, bilinear interpolation, bicubic interpolation, and lanczos interpolation are simple but the resulted image is blurred [8]. The learning-based algorithms main idea is that the lost details in (LR) images could be retrieved from a dictionary or a data set retrieved from fixed (HR) images set or website [11-13]. The reconstruction based algorithms enforce a constraint that the version of the estimated (HR) image should be consistent with its (LR) image according to predefined values [1].

The sections of paper are organized as follow. Section II presents image super resolution related techniques. Section III introduces a brief description about four compared techniques that are used in the comparison. Section IV describes the experimental results that show the advantages and disadvantages of each technique. Conclusion is presented in section V.

2. RELATED WORK

The authors in [14] proposed fast and robust multi frame super-resolution. This method based on normalization and Gaussian model. In normalization stage, the output images are generated with sharp edges. The sharp images are followed by Gaussian model to remove noise.

J. Sun et al [1] presented an image super-resolution using gradient profile prior. The gradient profile prior is learned from a huge number of natural images. It provides a constraint on image gradients when it estimates a high-resolution image from a low-resolution one. This gradient constraint helps to sharpen the details and putdown ringing along edges.

M. Bevilacqua et al [15] presented super-resolution through neighbour embedding. In this method the generation of a high-resolution image patch does not depend on only one of the nearest neighbours in the training set. Instead, it depends simultaneously on multiple nearest neighbours in a way similar to LLE for manifold learning.

The SR algorithms which depend on reconstruction-based require image patches from one or several images. This is achieved by registration and alignment of multiple LR image patches of the same scene with sub-pixel level accuracy [5], [7]. If the images haven"t insufficient patch self-similarity, these methods are not able to produce satisfying results [9]. A recent methods proposed in [17] moderate this limitation by learning image prior models via kernel principal component analysis from multiple image frames.

Another type of super resolution is learning based methods. The information is learned/observed from the training image data. Chang et al. [18] introduced the method of locally linear embedding (LLE) for super resolution dedications. Support vector regression (SVR) is proposed by Ni et al. [2] to fit the patches of low resolution image and the corresponding pixel value of the high resolution image in DCT and spatial domains. In order to achieve better SR results, one needs to carefully/manually select the training data. In such cases, the computation complexity of training and difficulty of training data selection take into account. Sparse Representation, it was first applied to SR by Yang et al. [8], [9]. They considered the image patch from HR images as a sparse representation with respect to an over-complete dictionary composed of signal-atoms. Kim and Kwon [19] proposed an example-based single image SR for learning the mapping function between the low and high resolution images by using sparse regression and natural image priors.

S. Derin et al [20] presented a novel Bayesian formulation for joint image registration and super resolution. The unknown high resolution image, motion parameters and algorithm parameters, including the noise variances, are modelled within a hierarchical Bayesian framework. The proposed framework can be extended to more general super resolution applications with more complex motion models. Y. Zhu et al [21] introduced a single image super resolution method using deformable patches. By considering each patch as a deformable field rather than a fixed vector, the patch dictionary is more expressive. This algorithm doesn"t have the ability for various of texture e.g. logo, animal, flowers.

Recently many researchers have been used sparse super-resolution algorithm for image interpolation and inpainting. Sparse super-resolution Estimators algorithm introduced a group of inverse problem estimators computed by mixing adaptively a group of linear estimators. Sparse mixing weights are calculated over a blocks of coefficients in a frame providing a sparse signal representation [22]. Computing adaptive directional image interpolations over a wavelet frame provides effective nonparametric of inverse problems. Curvelet frames and contour let frames build sparse image approximations by taking advantage of the image directional regularity. The instability of these algorithms come from their flexibility .Sparse super-resolution algorithm in [22] can be improved by Computing an adaptive signal representation in blocks. In which they are obtained as an adaptive mixing of linear Tikhonov estimators, over blocks of vectors in a frame. A fast orthogonal block matching pursuit algorithm is introduced to reduce the number of process by Applying of mixing directional interpolators over oriented blocks in a wavelet frame.

In spatial domain, multi-images SR algorithms are mostly working on aliasing artifacts that are present in LR images. The representative methods in this category include iterative back projection (IBP), Projection onto convex sets (POCS), Maximum Likelihood (ML). Iterative back projection (IBP) based method in [16] is initially a guess the HR targeted image. It is needed and then it is refined. A guess can be obtained by registering the LR images over an HR grid and then averaging them. This initial guess can be refined by using the simulated imaging model with a set of available LR observations. Then the error between the simulated LR images and the observed ones is obtained and back-projected to the coordinates of the HR image to improve the initial guess. In this method the back-projected error is the mean of the errors that each LR image causes.

3. COMPARED METHODS

This section describes four image super resolution methods. The compared methods that used in our comparative study are selected to be two states of art super resolution methods, and the other two are recently developed methods. The compared four methods are:

- Image Super-Resolution via Sparse Representation [2010] [9]
- Generative Bayesian Image Super-Resolution with Natural Image Prior [2012] [23]
- Super-resolution from Transformed Self-Exemplars [24]
- Deep Networks for Image Super-Resolution with sparse Prior [2015] [17]

3.1. Image Super-Resolution via Sparse Representation

Super resolution could be discussing from other point of view. J.Yang et al [9] introduced image super-resolution via sparse representation to generate SR based upon sparse representations by make training of coupled dictionaries from high and low resolution patch pairs. Let X is the high resolution image, Y the low resolution image, x the high resolution image patch, y the low resolution image patch, Dh dictionaries for high resolution and Dl dictionaries for low resolution. In order to recover the high resolution image (X), the method is based on two constrains. First constrain is the reconstruction constrain Y=SHX where S is down-sampling filter and H is blurring filter. Second constrain is Sparse prior, which patches (x) of the high resolution image (X) and patches (y) of low resolution image can represented like a sparse linear grouped in a dictionaries (Dh) and (Dl). The high resolution feature can be reconstructed as a combination of the sparse linear of the learned Dh dictionaries for high resolution atoms by assuming that low resolution and high resolution features share the same sparse recovered coefficients. The main disadvantage of this algorithm is the highly exhaustive computation caused by the used optimization function.

3.2. Generative Bayesian Image Super-Resolution with Natural Image Prior

In this method, initially a guess the high resolution image is needed and then it is refined. This guess can be obtained with the posterior mean, rather than the posterior mode [23] .To estimate the high resolution image, we take the advantage of sampling of high dimensional data for Gaussian Model and develop for MMSE for the HR image. In this method, Results compared with SR algorithms verify its effectiveness. This method has flexibility in using natural images priors in Bayesian model, and it use MCMC sampling based generative approach. The main drawback of this method is that it is not fast as MAP Solution.

3.3. Super-resolution from Transformed Self-Exemplars

The authors in [24] proposed an image super resolution method based on transformed self-exemplars. The algorithm produces the high resolution image by using the following steps:

1) Compute a transformation matrix T (homography) that warps target patch P to its best matching patch Q (source patch) in the down sampled image ID for each patch P in the low resolution image I. To obtain the parameters of such a transformation, we estimate a nearest neighbor field between image I and down sampled image ID using a modified Patch Match algorithm.

2) Extract the high resolution patch QH from the image I, which is the high resolution version of the source patch Q.

3) To obtain the self-exemplar PH, the inverse of the computed transformation matrix T to „unwarp" the high resolution patch QH, which is estimated HR version of the target patch P. After that, the algorithm paste PH in the HR image at the location corresponding to the LR patch P.

4) For all target patches, we repeat the above steps to obtain an estimation of the HR image.

5) Run the iterative back projection method to ensure that the estimated high resolution image satisfies the rebuilding constraint with the given low resolution.

Finally this method is difficulty conducting with fine details when the planes are not well detected. In addition to that, it is computationally complex due to the training procedure.

3.4. Deep Networks for Image Super-Resolution with Sparse Prior

Deep networks learning algorithms have been successfully applied in many areas of computer vision and image processing, including low-level image restoration issues. Several models depend on deep neural networks have been recently shown up for image super-resolution and gained better performance that overcome all previous invented models. We argue that domain expertise offered by the conventional sparse coding technique is still valuable, and how it can be concatenated with the key ingredients of deep networks learning to achieve further enhanced results. The method in [17] assumed that a sparse coding technique designed particularly for super-resolution could be shaped as a neural network, and trained in an ordered structure from end to end. The performance of the deep network based on sparse coding technique leads to much more efficient and effective training, as well as a reduced model size.

4. Experimental Results

We conducted a subjective evaluation of the super resolution results for several state of art methods, for comprehensive and fair comparison between the compared methods, they have been tested on a laptop with core i5 CPU and six GB of ram. To demonstrate the strengths and drawbacks of each of them, the comparison is done on the same dataset. According to the changes that happened to the super resolution image after resizing, it is very difficult to evaluate the quality by traditional objective evaluation such as pixel to noise ratio (PSNR). So, the quality depends on the human visual perception system rather than mathematical measures. Figure 1 shows an example of resizing low resolution face and natural images by using the four state-of-art methods. First row in figure 1 shows the original images. Second row shows the super resolution output from the method in [9]. The super resolution output from method in [23] is shown in third row. Fourth row introduces the super resolution output from method in [24]. Finally, Fifth row represents the super resolution output from method in [17].

In this comparative study, we conducted a mathematical quality measure by using PSNR. Therefore, we created artificial low resolution images. Then, we applied the four state-of-art methods to reconstruct the high resolution images from the artificial low resolution images. After that, we calculated the PSNR between the original high resolution images and the reconstructed high resolution images. Table I shows PSNR comparison for the images in figure 1. Table II presents processing time comparisons between the four methods for the images in figure 1.

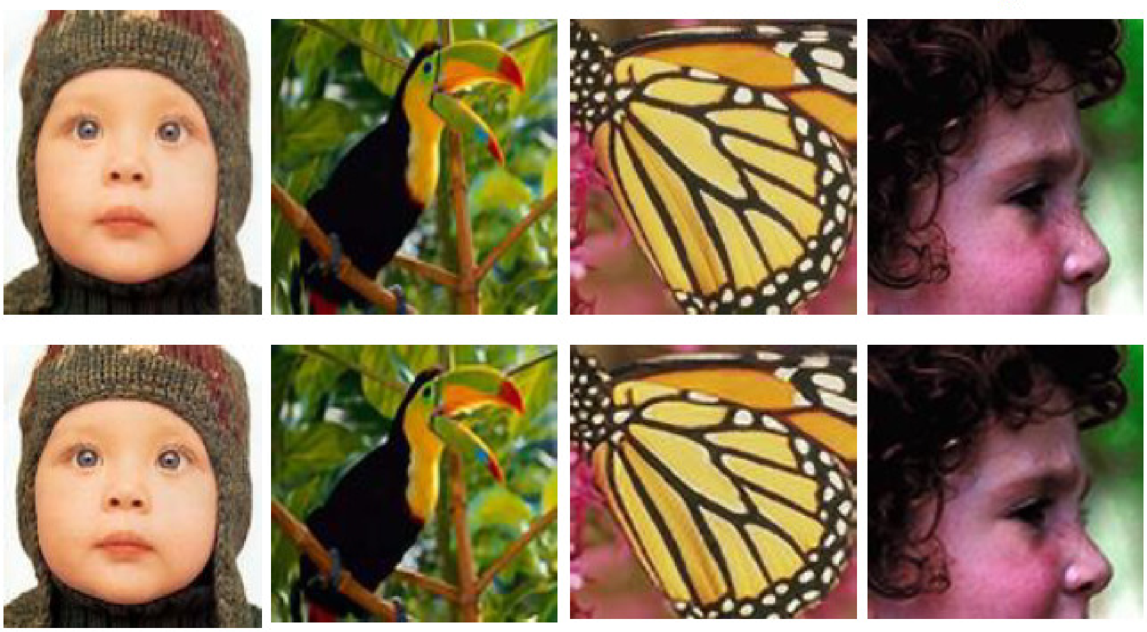
Table I. PSNR comparison between the four state-of-art methods.

IMAGE	SIZE	METHOD IN [9]	METHOD IN [23]	METHOD IN [24]	METHOD IN [17]
A	128X128	25.8	26.32	**28.12**	27.85
B	250X300	19.45	20.21	**23.31**	22.51
C	250X250	22.84	23.59	**25.53**	24.87
D	128X128	9.52	12.59	**13.21**	11.54

Table II. Processing time comparison between the four compared methods (in seconds).

IMAGE	SIZE	METHOD IN [9]	METHOD IN [23]	METHOD IN [24]	METHOD IN [17]
A	128X18	540	12	7.32	6.33
B	250X300	286	8.84	163.23	4.22
C	250X250	170	5.5	152.45	3.84
D	128X128	125	3.2	3.52	1.95

A B C D



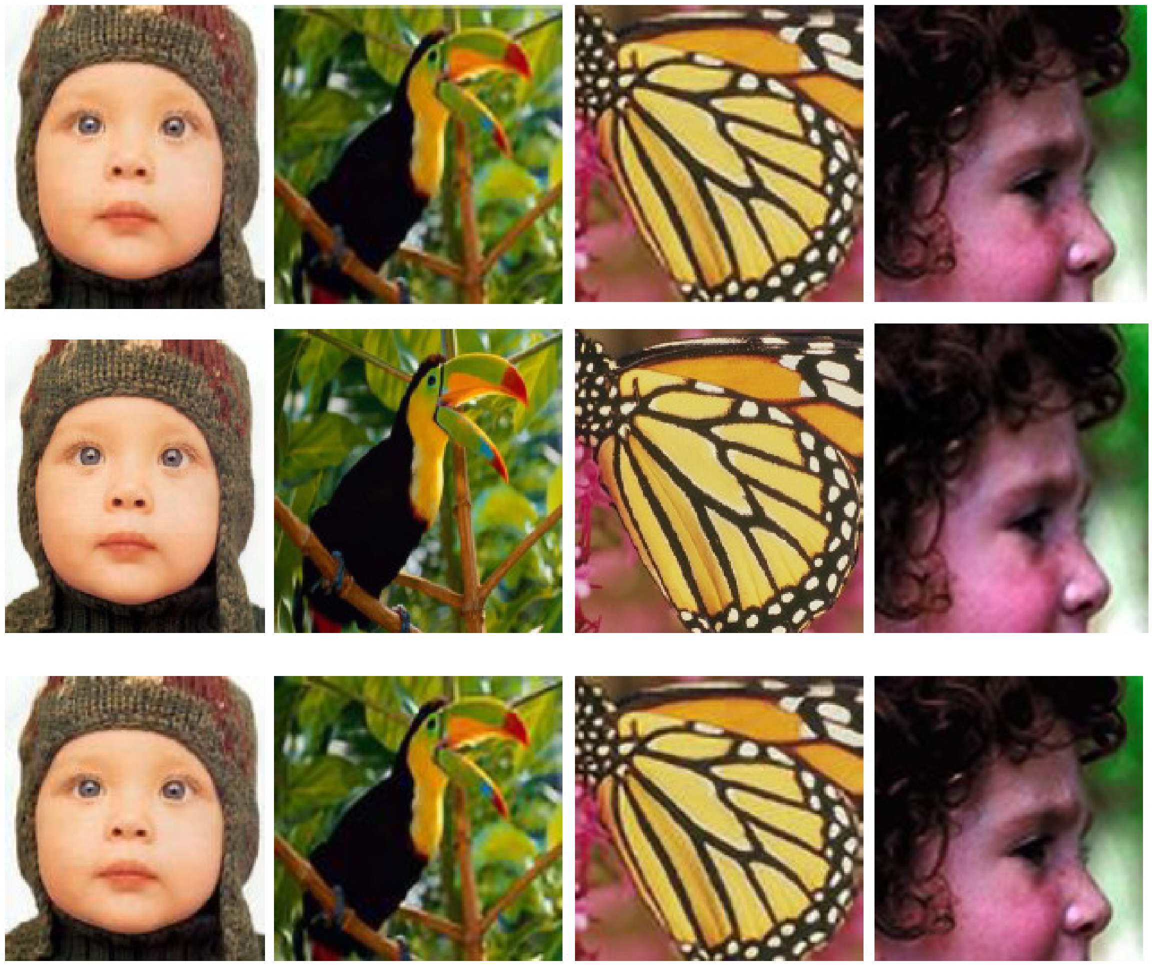


Figure. 1 Examples of recovering super resolution images. Row 1 represents the original images, row 2 represents the results of method [9], row 3 represents the results of method [23], row 4 represents the results of method [24], and row 5 represents the results of method [17].

5. CONCLUSIONS

In this research paper, we introduce image super resolution comparative study between four recent methods. We conducted to be fair as much as possible by comparing the four image super resolution methods in the same images as well as device hardware. The experimental results illustrate the strengths and drawbacks of each method. According to the PSNR table and Time table we can conclude that, Method [24] produces the higher PSNR value over the other methods. In the second table Method [17] produces the minimum Time. Therefore, we recommend them for all researchers to be applied in their super resolution applications future work.

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