ISSN - 2348-2397
APPROVED UGC CARE

SHODH SARITA
Vol. 7, Issue 26, April-June, 2020
Page Nos. 112-117

AN INTERNATIONAL BILINGUAL PEER REVIEWED REFEREED RESEARCH JOURNAL

ENHANCING THE RESOLUTION AND PERCEPTUAL QUALITY OF IMAGES BY SUPER-RESOLUTION

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ABSTRACT

A robust single-image **super-resolution** (SR) method in the compression scenario, which is competent for simultaneously increasing the resolution and perceptual quality of web image with different content and degradation levels. Super resolution terms such as "upscale", "upsize", "up-convert" and "uprez" also describe increase of resolution in either image processing editing. **First, propose to analyze the imageenergy change characteristics during the iterative regularizationprocess, i.e., the energy change ratio between primitive and non-primitive fields. Based on thereviled convergence property of the energy change ratio, appropriateregularization strength can then be determined to wellbalance compression artifacts removal and primitive components preservation. Consequently, their combination effectively eliminates the quantization noise and meanwhile faithfully compensates the missing high-frequency details, yielding powerful super-resolution performance in the compression scenario.** The algorithm attempts to recognize local features in the low resolution images and then enhances their resolution in an appropriate manner. Enhancements treated here include improvement of image resolution, **perceptual quality** of objects.

Keywords : super-resolution (SR), **convergence**.

1. INTRODUCTION

In most digital imaging applications, high resolution images or videos are usually desired for image processing and analysis. The desire for high image resolution stems from two principal application areas: improvement of pictorial information for human interpretation and helping representation for automatic machine perception. Image resolution describes the details contained in an image, the higher resolution, and the more image details.

The main aim of the paper is to investigate the **robust single-image super-resolution method for enlarging low quality web image/video degraded by down sampling and compression.** There is a large demand for improving the perceptual quality of web image/video, among which the resolution enhancement, also known as super-resolution (SR), is an especially important issue and attracts a lot of attention. SR refers to the techniques achieving high-resolution (HR) enlargements of pixel-based low-resolution (LR) image/video.

1.1. Image Processing

Image processing pertains to the alteration and analysis of pictorial information. Common case of image processing in real time is the adjustment of brightness and contrast controls in a television set, by doing this we enhance the image unless and until it is appealing to the human eye. The biological system (eye, brain) receives, enhances, analyses and stores images at enormous rates of speed. Processing of digital images by means of digital computer refers to Digital Image Processing (DIP). Digital images are composed of finite number of

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elements which has a particular location value. DIP generally refers to processing of a two dimensional images by a digital computer. In simple words an image is a representation of a real scene, either in black and white or in colour, and either in print form or in a digital form i.e., technically an image is a two-dimensional light intensity function.

A digital image is an array of real or complex numbers represented by a finite number of bits. Images now play a crucial role in fields as diverse as medicine, journalism, advertising, design, education and entertainment. Technology in the form of inventions such as photography and television has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging evolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission.

2. OBJECTIVE

This method combines adaptive PDE regularization with learning-based pair matching to eliminate the compression artifacts and meanwhile best preserve and enhance the high-frequency details.

The goal of color and contrast enhancement in general is to provide a more appealing image with vivid colors and clarity of details. These enhancements are intimately related to different attributes of visual sensation. **The efficiency of the method is shown on various radiometric modifications: contrast equalization, midway histogram, color enhancement, and color transfer.**

- **It's increasing the resolution & perceptual quality of web image.**
- **Proposed an efficient way to combine PDE regularization & learning based SR.**
- **We extended this method for video with certain interface interaction and simple spatio-temporal coherency optimization.**
- **This method is works on both offline & online tests to validate the effectiveness.**
- **Due to robust performance & low complexity itsprovide practical enlarge -preview tool for thumbnail web image.**

3. REVIEW OF LITERATURE

With the Internet flourishing and the rapid progress in hand-held photographic devices, image and video are becoming more and more popular on the web, due to their rich content and easy perception. Consequently, image search engines and online video websites have experienced an explosion of visits during the past few years. However, limited by the network bandwidth and server storage, most web image/video exists in a low quality version degraded from the source. The most common degradations are down-sampling and compression.

Down-sampling exploits the correlation in the spatial domain while compression further exploits the correlation in the frequency and temporal (for video) domains. Quality degradation greatly lowers the required bandwidth and storage, making the access to web image/video practical and convenient. But these benefits are obtained at the expense of impairing the perceptual experience of users, as degradation inevitably leads to information loss, which behaves as various artifacts in the resulting image/video, e.g., blurring, blocking and ringing.

Despite great diversity in implementation, these methods have a common premise that the LR image is only degraded by down-sampling. This is not always true in the web environment, where compression is widely adopted. For image search engines, compression helps reduce the thumbnail size by up to 50% without obvious perceptual quality loss when presented in the LR form. But now if SR (any of the above) is directly performed, compression artifacts will be magnified out and the perceptual quality of resulting HR images will be poor.

4. METHODOLOGIES

3.1 Resolution of Image

When taking an image with a digital camera, or digitizing a video sequence, the following problem arises: the information that we photograph has to be discredited and reflected in pixels so that it can be represented in a computer. We thus lose both spatial information and information of each pixel intensity. Graphically, the following images show a simulated example

Figure 3.1 Image to be photographed

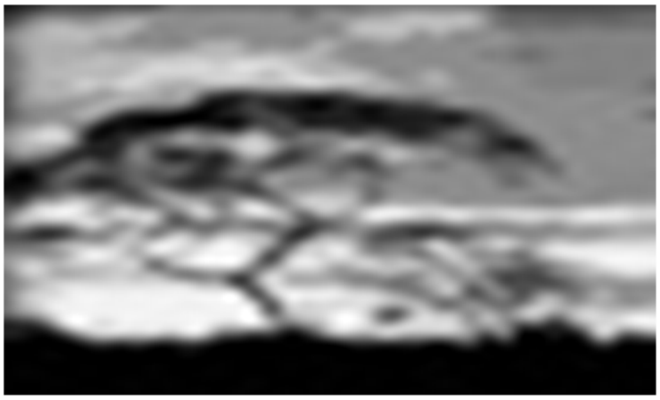

Figure 3.2 Digitalized Image

Notice how the information has been lost in both senses (space and intensity of each pixel) even though the example has been taken to the extreme, it is not unusual that video film images taken with security cameras are of poor quality. To this problem some other complications are added, such as noisy images, blurred images, out of focus, etc.

3.2 Enhancing an image

The simplest way of obtaining a basic enhancement in an image resolution is applying this image to some of the so-called interpolation techniques. The most popular are bi-cubic, bilinear, and the nearest neighbor technique (here mentioned decreasingly, taking into account the quality of the result obtained). Even though such methods present a fast solution, this is not enough in surveys, in which the certainty of the observed information in the image must be the highest. Although there exist some other methods that allow achieving an even greater enhancement, there are yet not enough to the effects of obtaining a significant optimization.

3.3 Taking advantage of an image sequence

Image Super-Resolution which is based on taking advantage of non-redundant information of a video sequence in order to obtain as result an image of higher resolution. Super-Resolution allows minimizing the discretization problem and the quantification error. The first problem can be summed up as the dilemma of determining in which pixel certain part of the photographed image should be placed; whereas the second problem is presented when we have to decide how intense such pixel should be, taking into account that we have a finite number of values that can be assigned to. Figure 3.3 depicts the first problem. We can easily determine that the gray point must be stored in position (3, 4) of the pixel matrix that makes up the image. But, where should the black point bestored?

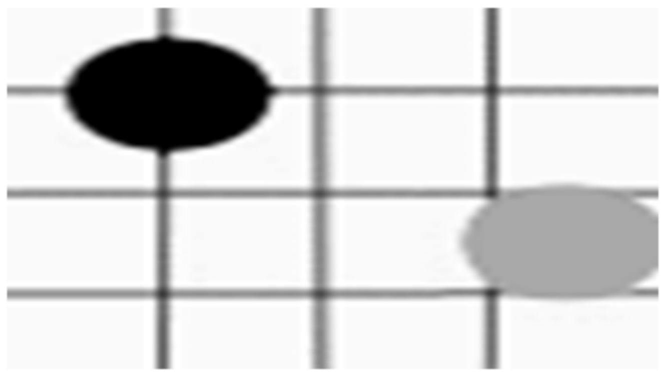

Figure 3.3 Two points that should be reflected in the image

Figure 3.3 shows the quantification problem. Assuming that a pixel (x, y) of an image deserves an intensity level of 122.6, such pixel will have to be stored with level 123, though this may not correspond to the observed value.

1. DATAANALYSIS

An overview of our single-image SR scheme in the compression scenario is shown in Fig. 1. Suppose Xo is an original HR image, it is first down-sampled with a low-pass filter (mostly isotropic Gaussian) to form an LR measurement Yo

$$Y0=(g*x0)\downarrow^{a} \qquad (1)$$

Where $\downarrow^{a}$ is a decimation operator with scaling factor a.Y0 is then compressed, resulting in a degraded LR measurement

$$Y=Y0+EQ \qquad (2)$$

Where EQrepresents the quantization error introduced by compression in the spatial domain.Y is the actual input of our SR system. This system consists of three modules: Partial differential equation(PDE) regularization, bicubic interpolation and learning-based pair matching. Regularization is first performed on to get an artifacts-relieved LR image Y*

$$Y^* = \oint^{N}(Y) \qquad (3)$$

Where $\oint^{N}$ Denotes the PDE regularization functional and the superscript represent the total iteration number of regularization, which determines the regularization strength. Y* is then up-sampled with scaling factor to get an intermediate HR result X*

$$X^* = (h^*(Y^*))\uparrow^{b} \qquad (4)$$

Where h stands for the bicubic interpolation filter. The final HR image is obtained after learning-based pair matching from X*and a prepared database. The maximum a posterior (MAP) probability X estimate of can be expressed as

$$X = \operatorname{argmax}_x \; p((X|X^*, D)) \qquad (5)$$

Algorithm Implementation :

Algorithm : The algorithm for compressed image SR is as follows :

Input : Compressed Low resolution image Y

Output : Enhanced high resolution image X (i.e. SR)

START

1. Perform up sampling Y to X_o* using Bicubic interpolation
2. Find the Edges (primitive field) and non-edge portion (Non primitive fields) partitioned (P,Q) of X_o* through the orientation energy edge detection.
   2.1 perform PCA based training
3. Perform iterative PDE regularization on Y:
   3.1 After each iteration, up-sample the regularized image Y_n* to X_n*, where n=1,2,…….through Bicubic interpolation;
   3.2 Calculate the image energy change based on the PF/NPF partition
   3.3 Calculate the energy change ratio between PF and NPF
   3.4 Find the maximum value of ratio
   3.5 mention a condition to stop regularization
4. Extract LR primitive patches from and find corresponding HR primitive patches from a prepared database through pair matching speeded up by the approximate nearest neighbor (ANN) tree searching.
5. Add the HR primitive patches back to X_N* to form the final HR image X, where the compatibility of neighboring HR primitive patches is enforced by averaging the pixel values in overlapped regions.

5. RESULTS

In Bayesian statistics, a Maximum A Posteriori probability (MAP) estimate is a mode of the posterior distribution. The MAP can be used to obtain a point estimate of an unobserved quantity on the basis of empirical data. And Mean Squared error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss.

The term **Peak Signal-to-Noise Ratio (PSNR)** is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Because many signals have a very wide **dynamic range**, (ratio between the largest and smallest possible values of a changeable quantity) the **PSNR** is usually expressed in terms of the logarithmic decibel scale.Image enhancement or improving the visual quality of a digital image can be subjective. Saying that one method provides a better quality image could vary from person to person. For this reason, it is necessary to establish quantitative/empirical measures to compare the effects of image enhancement algorithms on image quality.

Using the same set of tests images, different image enhancement algorithms can be compared systematically to identify whether a particular algorithm produces better results. The metric under investigation is the **peak-signal-to-noise ratio**. If we can show that an algorithm or set of algorithms can enhance a degraded known image to more closely resemble the original, then we can more accurately conclude that it is a better algorithm.The **structural similarity** (SSIM) index is a method for measuring the similarity between two images.**Root-mean-square error (RMSE)** is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed.

5.1 Algorithm in test : AR

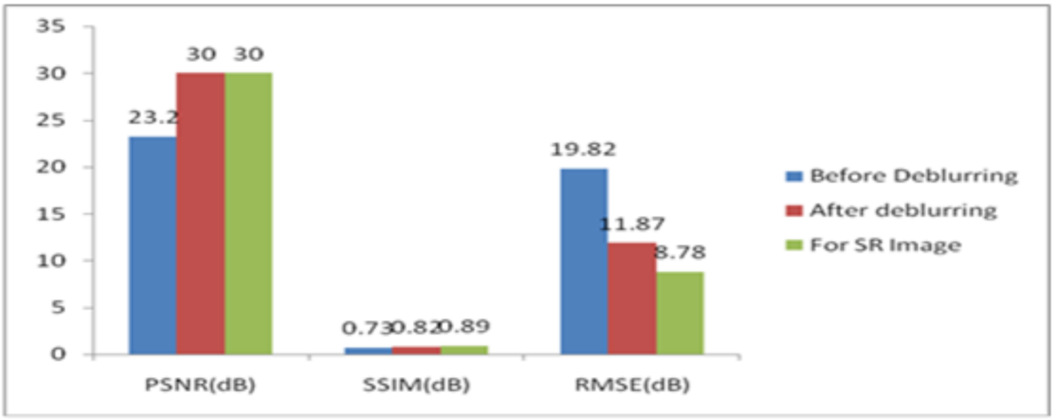

Fig.5.1(a) Combination for Test A-C-E-H in AR Algorithm

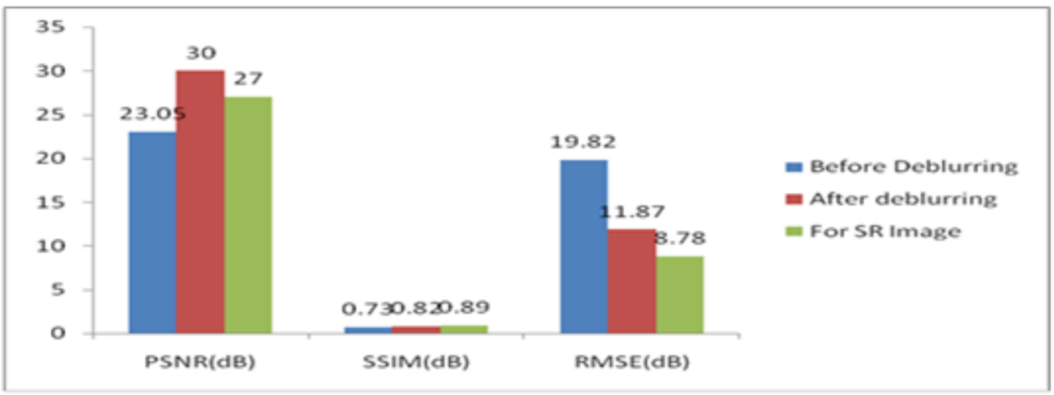

Fig.5.1(b) Combination for Test B-C-E-H in AR Algorithm

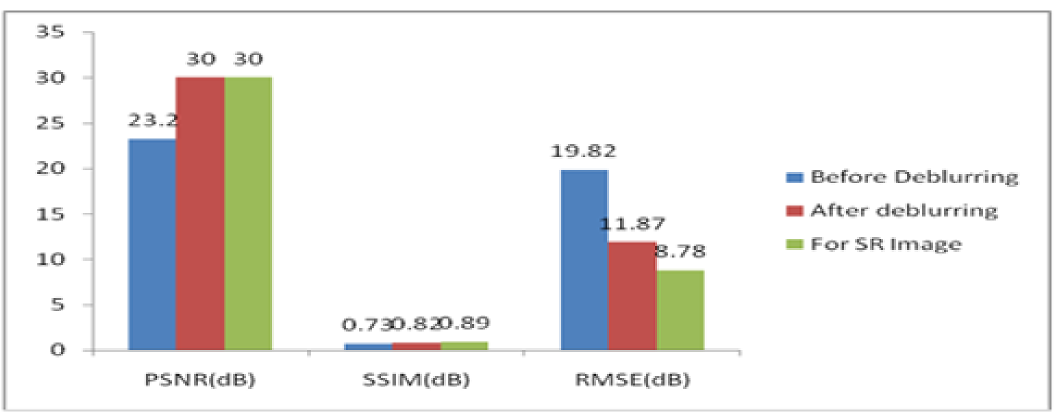

Fig.5.1(c) Combination for Test A-D-E-H in AR Algorithm

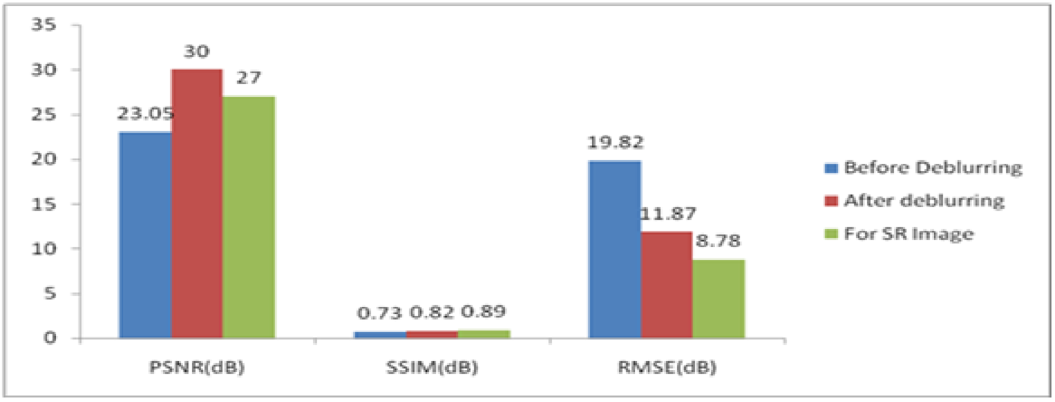

Fig.5.1(d) Combination for Test B-D-E-H in AR Algorithm

6. CONCLUSION

A robust single-image SR method in the compression scenario, which is capable for simultaneously increasing the resolution and perceptual quality of web image/video with different content and degradation levels. This method combines adaptive PDE regularization with learning-based pair matching to eliminate the compression artifacts and meanwhile best preserve and enhance the high-frequency details. As learning-based SR is usually performed at patch level and relatively noise-sensitive, we then prefer a global algorithm for compression artifacts removal to avoid local inconsistency (i.e., adjacent regions should be stably smoothed).

This method can be naturally extended to video with certain interface interaction and simple spatio-temporal coherency optimization. Experimental results, including both offline and online tests, validate the effectiveness of our method. Due to its robust performance and low complexity, our solution provides a practical enlarge-preview tool for thumbnail web images, especially those provided by image search engines; it may also be applied to video resizing for online video websites, in case more powerful computational resources (e.g., GPU) are available.

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