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A Novel Image Super-Resolution

K. Rajesh Kumar[1], A.N. Sai Chakravarthy[2]

Assistant Professor, Dept of ECE, Keshav Memorial Institute of Technology, Hyderabad, Telangana, India[1]

Assistant Professor, Dept of ECE, Keshav Memorial Institute of Technology, Hyderabad, Telangana, India[2]

ABSTRACT: Super-resolution (SR) image reconstruction is the process ofcombining several low resolution images into a single higherresolution image or Generating high resolution image from a single low resolution image. There is a driving need for digital images ofhigher resolutions and quality.In order to improvethe resolution and perceptual quality of such web image/video, webring forward a sensible solution which mixes adaptive regularization and learning-based super-resolution. The contributionof this work is twofold. First, we tend to propose to research the imageenergy modification characteristics during the iterative regularizationprocess, i.e., the energy change magnitude relation between primitive (e.g., edges, ridges and corners) and non-primitive fields supported therevealed convergence property of the energy modification magnitude relation, acceptable regularization strength will then be determined to wellbalance compression artifacts removal and primitive elementspreservation. Second, we tend to verify that this adaptive regularizationcan steady and greatly improve the try matching accuracy inlearning-based super-resolution.

KEYWORDS: Adaptive regularization, compression artifacts removal, energy change ratio, learning-based super-resolution (SR).

I. Introduction

High-resolution images or videos are required in most digital imaging applications. Higher resolution offers an improvement of the graphic information for human perception. It is also useful for the later image processing, computer vision etc. Image resolution is closely related to the details included in any image. In general, the higher the resolution is, the more image details are presented.Super-resolution, loosely speaking, is the process of recovering a high-resolution image from a set or single low resolution input image. Any given set of source low resolution (LR) images only captures a finite amount of information from a scene; the goal of SR is to extract the independent information from each image in that set and combine the information into a single high resolution (HR) image (Pair Matching). The only requirement is that each LR image must contain some information that is unique to that image. This means that when these LR images are mapped onto a common reference plane their samples must be subpixel shifted from samples of other images – otherwise the images would contain only redundant information and SR reconstruction would not be possible. Most methods in SR are strictly reconstruction based; that is, they are based primarily on uniform and nonuniform sampling theorems and do not attempt to create any information not found in the LR images. There are also learning SR methods that create new information based on generative models.

SR techniques can prove useful in many different applications, and these applications can have different requirements in terms of both quality and computational complexity. The quality may also vary for different methods based on characteristics of the input image. The implementation complexity may be affected by implementation specifics, such as the availability of specific optimized libraries. Finally the artifacts caused by poor SR performance can be more visually distracting than blurring from interpolation. For these and other reasons choosing between SR methods is a complex task. A variety of approaches for solving the super-resolution problem have been proposed. Initial attempts worked in the frequency domain, typically recovering higher frequency components by taking advantage of the shifting and aliasing properties of the Fourier transform. Deterministic regularization approaches, which work in the spatial domain, enable easier inclusion of a priori constraints on the solution space (typically with smoothness prior). Stochastic methods have received the most attention lately as they generalize the deterministic regularization approaches and enable more natural inclusion of prior knowledge. Other approaches include non-uniform interpolation, projection onto convex sets, iterative back projection, and adaptive filtering. With the increased emphasis on stochastic techniques have also come increased emphasis on learning priors from example data rather than relying on more

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heuristically derived information.To further improve the robustness of such an approach, we propose a more solid criterion for the adaptive regularization control in this work, based on the convergence property of the image energy change ratio between primitive and non-primitive fields during iterative regularization By appropriately locating the turning point where regularization loses its efficacy in distinguishing primitive components from compression artifacts, the pair matching accuracy in learning-based SR can be steadily and greatly improved. In this way, the quantization noise is effectively eliminated while the missing high-frequency details are faithfully compensated. Moreover, the proposed single-image SR method can be directly applied into compressed video SR, by introducing certain interframe interactions on the regularization strength and simple spatial-temporal consistency optimization, as reported in our latest work [11]. Previous work on single-image SR can be roughly divided into four categories: interpolation-based [1]–[4], reconstruction-based [5], [6], classification-based [7] and learning-based [8]–[10].

II. RELATED WORK

There are many different methods available for SuperResolution Image Reconstruction. We did comparisonof some of the methods available. Algorithms are asfollows:

Nonuniform Interpolation

This approach is the most intuitive method for SRimage reconstruction. In this approach three stagesare performed successively.

1. Relative motion is estimated, i.e., registration if themotion information is not known.
2. Nonuniform interpolation is done to produce animproved resolution image, and
3. Process of deblurring is done depending on theobservation model.

Non-uniform interpolation has relatively lowcomputational complexity and it assumes that theblur and noise characteristics are identical across allLR images. The HR image on non-uniformly spacedsampling points is obtained with the relative motioninformation estimated. Then, the director iterativereconstruction procedure is followed to produceuniformly spaced sampling points. Once an HRimage is obtained by non-uniform interpolation, wetackle the restoration problem to remove blurring andnoise.

2.2 Frequency Domain

Aliasing which exists in all LR images is explicitlyused to reconstruct HR image. Tsai and Huang [1]first derived a system equation that describes therelationship between LR images and a desired HRimage by using the relative motion between LRimages. The frequency domain approach is based onthree principles:

1.The shifting properties of the Fourier transform.

2.The aliasing relationship between the continuousFourier transform (CFT) of an original HR image andthe discrete Fourier transform (DFT) of observed LRimages.

3.The assumption that an original HR imageis band limited.

These properties make it possible to formulate thesystem equation relating the aliased DFT coefficientsof the observed LR images to a sample of the CFT ofan unknown image. Main advantage of the frequencydomain approach is theoretical simplicity, it meansthe relationship between LR images and the HRimage is clearly demonstrated in the frequencydomain. This method is also convenient for parallelimplementation capable of reducing hardwarecomplexity.

2.3 Nearest Neighbor algorithm

The Nearest Neighbor interpolation is the fastest andsimplest option. It simply takes the color of a pixeland assigns it to the new pixels that are created fromthat pixel. Due to this simplistic approach, it does notcreate an anti-aliasing effect. This leads to problems with jaggies. Consequently, Nearest Neighborinterpolation is considered to be incapable ofproducing photographic quality work. It selects thevalue of the nearest pixel by rounding the coordinatesof the

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desired interpolation point x ⩾ 0.With anobvious extension to the two-dimensional case. Let⌊·⌋ is the floor operator: the largest integer less than or equal to the argument. As a result of this simplisticinterpolation scheme, nearest neighbor doesn't havesub pixel accuracy and generates strongdiscontinuities, especially when arbitrary rotationsand scale changes are involved. The only interestingproperty of this algorithm is the fact that it preservesthe original noise distribution in the transformedimage, which can be useful in some image analysisapplications. This is most commonly used in-camerawhen reviewing and enlarging images to view details.

It simply makes the pixels bigger, and the color of anew pixel is the same as the nearest original pixel.2.4 Bilinear Interpolation algorithmBilinear interpolation uses the information from apixel (let's call it the original pixel) and four of thepixels that touch it to determine the color of the newpixels that are created from the original pixel.

Bilinear uses rather simple, linear calculations to dothis. The Bilinear interpolation does have an antialiasing effect. However, it is not considered goodenough for photo quality images. This takes theinformation from an original pixel, and four of thepixels that touch it, to decide on the color of a newpixel. It produces fairly smooth results, but it reducesthe quality significantly. Images can become blurry.

2.5 Bicubic Interpolation algorithm

Bicubic interpolation uses the information from anoriginal pixel and sixteen of the surrounding pixels todetermine the color of the new pixels that are createdfrom the original pixel. Bicubic interpolation is a bigimprovement over the nearest neighbor interpolationand bilinear interpolation methods for two reasons:

(1) Bicubic interpolation uses data from a largernumber of pixels and

(2) Bicubic interpolation uses aBicubic calculation that is more sophisticated thanthe calculations of the previous interpolationmethods. Bicubic interpolation is capable ofproducing photo quality results and is probably themethod most commonly used. This is the mostsophisticated of the bunch, as it takes informationfrom the original pixel and 16 surrounding pixels tocreate the color of a new pixel. Bicubic calculation isfar more advanced than the other two methods, and itis capable of producing print quality images. Bicubicinterpolation also offers the two variants of"Smoother" and "Sharper" for finely tuned results

III. PROPOSED ALGORITHM

An overview of our single-image SR scheme in the compression scenario is shown in Fig. 1. Suppose X_0 is an original HRimage, it is first downsampled with a low-pass filter (mostly isotropic Gaussian) to form an LR measurement $Y_{0.}$

$Y_0 = (g * X_o) \downarrow^{\alpha}$……………………….. (1)

Where g is a decimation operator with scaling factorα.$Y_0$is then compressed, resulting in a degraded LR measurement Y

$Y = Y_0 + E_Q$…………………………. (2)

Where E_Q represents the quantization error introduced by compression in the spatial domain.

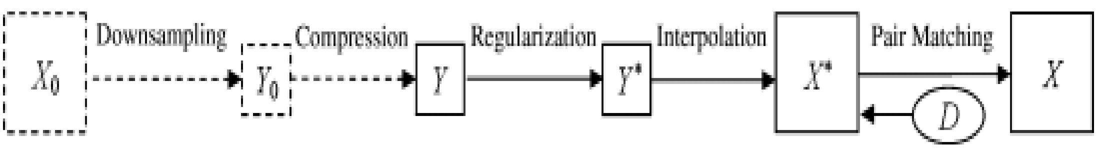

Fig. 1. Flowchart of our compressed image super-resolution scheme.

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Y is the actual input of our SR system. This system consists of three modules: PDE regularization, bicubic interpolation and learning-based pair matching. Regularization is first performed on Y to get an artifacts-relieved LR image Y^*

$Y^* = f^N(Y)$............................. (3)

Where$f(*)$denotes the PDE regularization functional and thesuperscript N represents the total iteration number of regularization, which determines the regularization strength.$Y^*$is thenupsampled with scaling factor β to get an intermediate HR resultX^*

$X^* = (h * Y^*) \uparrow^{\beta}$.............................. (4)

where h stands for the bicubic interpolation filter. The final HR image X is obtained after learning-based pair matching from $X^*$and a prepared database D.

PDE Regularization

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It consists in simplifying knowledge in a manner that only fascinating options are preserved. With this type of model, regularizing the image we will be similar to find a smooth surface. This may be done by directly designing PDE's (Partial Differential Equation) with specific regularization behaviours that evolve the noisy surface.Using regularization terms R in PDE's formulations like ∂I/∂t=R, the data are iteratively regularized and a continuous sequence of smoother image I(t) is generated whereas the evolution time t goes by. A desired behaviour of such regularization algorithms is that the less significant data features disappear first, while the Interesting ones are preserved as long as they become unimportant themselves within the image.The isotropic regularization behaves like a low-pass filter suppressing high frequencies in the image. Unfortunately, image edges are high frequency signals as well as noise, so edges are eliminated. The need to find anisotropic regularization methods has then quickly appeared (in particular for image restoration purposes).

Therefore, isotropic diffusion smooths with equal strength in all directions and edges in the image will soon become blurred. Also, Heat equation is used for isotropic equation, given by

ΔI= 〖∂I/∂t=I〗 _xx+I_yy (5)

For n iteration the edges are added to the initial image, using the following regularization

In=In-1+ λ*∂I/∂t (6)

Where,

In is the end resulting image after isotropic PDE smoothing.

In-1 is the initial image

∂I/ ∂t or ΔI is given by equation 1.

λ is the positive constant controlling the updating step.

Anisotropic PDE Regularization smooths the image and retains edges, i.e. smoothing is done along the edges not across it. Anisotropic smoothing can be viewed as joining of two 1D heat flows along the gradient direction and the isophote direction. Isophote are lines of equal light intensity. Note that ξ is everywhere tangent to the isophote lines I(x, y) = a, i.e. to the contours in the image. The set (ξ, η) is then a moving orthonormal basis whose configuration depends on the current point coordinates (x, y).

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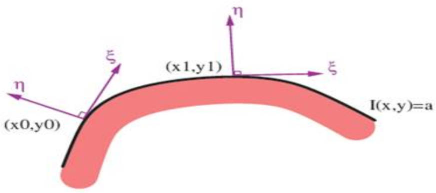

Fig.2 An image contour and its moving vector basis (ξ, η)

The anisotropic Partial Differential Equation (PDE) is given by

$$\frac{dI}{dt} = C_\xi I_{\xi\xi} + C_\eta I_{\eta\eta} \tag{7}$$

Where,

$$I_{\xi\xi} = \frac{\partial^2 I}{\partial \xi^2} = \frac{i_x^2 - 2 * i_x * i_{xy} * i_y + i_y^2 * i_{xx}}{i_x^2 + i_y^2} \tag{8}$$

Where as $\frac{\partial^2 I}{\partial \eta^2}$ can be obtained by taking the orthogonal of $\frac{\partial^2 I}{\partial \xi^2}$, as both are in orthogonal direction. $\frac{\partial^2 I}{\partial \xi^2}$ computes the second order directional derivative of image I in the direction of ξ, which is opposite to gradient direction. $\frac{\partial^2 I}{\partial \eta^2}$ Computes the second order directional derivative of image I in the direction of ξ, which is in the gradient direction.

Pair Matching

The goal of the pair matching is to estimate the missing high-resolution details that aren't present in the interpolated image and which can't be visible by simple sharpening.To demonstrate the necessity and effectiveness of adaptiveregularization in compressed image SR with learning-basedmethods, we then investigate the pair matching accuracy underthree different circumstances, i.e., without compression, withcompression but no regularization and with both compressionand adaptive regularization.

IV. RESULTS AND DISCUSSIONS

We test our SR scheme on both offline images degraded by designated down sampling and compression from the sources, as well as compressed thumbnail images on the web.

(a) (b) (c)

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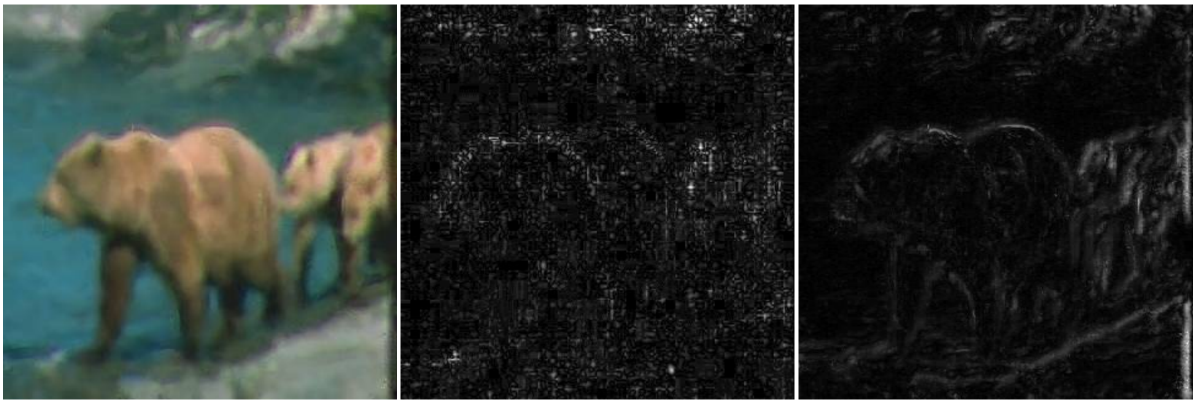

(d) (e) (f)

(g) (h)

Fig.3 (a) Input image (b) Bicubic interpolation (factor of 2) (c) Anisotropic PDE regularization
(d) Pair matching (e) Difference between (b) & (c) (f) Difference between (b) & (d)
(g)Original image zoomed (h) Anisotropic smoothed version of zoomed image

V. CONCLUSION

In this paper, we tend to present a robust single-image SR technique in the compression situation that is competent for at the same time increasing the resolution and perceptual quality of web image/video with completely different content and degradation levels. Our technique combines adjustive PDE regularization with learning-based pair matching toeliminate the compression artifacts and in the meantime best preserve and enhance the high-frequency details.

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BIOGRAPHY

K. Rajesh Kumar completed his M.Tech in the stream of M.Tech (SSP). He is having teaching experience of more than 2 years in various Under Graduate and Post Graduate course. At present, he is working as Assistant Professor, Dept. of ECE, Keshav Memorial Institute of Technology, Hyderabad, Telangana, India.

A.N. Sai Chakravarthy completed his M.Tech in the stream of M.Tech (VLSI SD). He is having teaching experience of more than 2 years in various Under Graduate and Post Graduate course. At present, he is working as Assistant Professor, Dept. of ECE, Keshav Memorial Institute of Technology, Hyderabad, Telangana, India.