Super Resolution of Single Image using Interpolation Techniques

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Abstract— Image super-resolution (SR) is a commonly used technique to solve the mismatch between the high quality devices such as television and smart phones and the low resolution (LR) sources. Unfortunately, image SR methods are suitable for natural images and leads to blocking artifacts. In this paper, we propose a simple interpolation technique which consists of three step process such as basic filtering process, encoding, decoding process and an interpolation process Experimental results on various single images indicates that the proposed method can effectively reproduce the SR results with better visual quality. Furthermore, the parameters such as SNR, PSNR and MSE values also improved with reasonable computational time.

Key words: Super Resolution, Interpolation Techniques and Visual Quality

I. Introduction

Image resolution describes the details contained in an image, the higher the resolution the more image details. The resolution of a digital image can be classified in many different ways: pixel resolution, spatial resolution, spectral resolution, temporal resolution, and radiometric resolution. Super resolution reconstruction is a promising technique of digital imaging which attempts to reconstruct HR images by fusing the partial data contained within a number of under sampled low resolution (LR) images of that scene during the image reconstruction process. Super resolution reconstruction involves up sampling of under sampled images thereby filtering out distortions such as noise and blur. In comparison to various image enhancement techniques, super resolution reconstruction technique not only improves the quality of under sampled, low resolution images by increasing their spatial resolution but also attempts to filter out the unwanted distortions. Super-resolution (SR) are techniques that construct high-resolution (HR) images from several observed low-resolution (LR) images, thereby increasing the high frequency components and removing the degradations caused by the imaging process of the low resolution camera. The basic idea behind SR is to combine the non-redundant information contained in multiple low-resolution frames to generate a high-resolution image. A closely related technique with SR is the single image interpolation approach, which can be also used to increase the image size. However, since there is no additional information provided, the quality of the single image interpolation is very much limited due to the ill-posed nature of the problem, and the lost frequency components cannot be recovered. In the SR setting, however, multiple low-resolution observations are available for reconstruction, making the problem better constrained. The non-redundant information contained in these LR images is typically introduced by sub pixel shifts between them. These sub pixel shifts may occur due to uncontrolled motions between the imaging system and scene, e.g., movements of objects, or due to controlled motions, e.g., the satellite imaging system orbits the earth with predefined speed and path. Each low-resolution frame is a decimated, aliased observation of the true scene. SR is possible only if there exists sub pixel motions between these low resolution frames, and thus the ill-posed up sampling problem can be better conditioned. In the imaging process, the camera captures several LR frames, which are down sampled from the HR scene with sub pixel shifts between each other. SR construction reverses this process by aligning the LR observations to sub pixel accuracy and combining them into a HR image grid (interpolation), thereby overcoming the imaging limitation of the camera. Many techniques have been proposed over the last two decades, representing approaches from frequency domain to spatial domain, and from signal processing perspective to machine learning perspective. Early works on super-resolution mainly followed the theory of by exploring the shift and aliasing properties of the Fourier transform. However, these frequency domain approaches are very restricted in the image observation model they can handle, and real problems are much more complicated. Researchers nowadays most commonly address the problem mainly in the spatial domain, for its flexibility to model all kinds of image degradations.

II. Literature survey

T. Goto et al (2014) presented the super-resolution system for 4K-HDTV. In this paper, we've bent to propose a totally distinctive account 4K-HDTV system. The super-resolution system consists of whole variation (TV) regularization decomposition, a shock filter, and a pulse improvement filter, and conjointly the compression noise removable system consists of the TV regularization decomposition and a de blocking edge filter (DEF). We've a bent to urge smart ends up in terms of image quality which we have a tendency to implement our system on GPGPU, which we have a tendency to bring home the bacon every noise exclude and super-resolution from Full-HD to 4K-HD resolution conversion in real time we've a bent to ponder this method to be a smart answer, significantly for the super-resolution of television broadcasting signal for devices like 4K-HDTV receivers and PCs with 4K show panels.

L. Kang et al (2015) pronounced the Learning-Based Joint Super-Resolution and Deblocking for an extremely Compressed Image. In this paper, a very compressed image is typically not only of low resolution, but to boot suffers from compression units (blocking whole thing is treated as Associate in nursing example throughout this paper). In this paper, we have a tendency to tend to propose a singular learning-based framework to achieve joint single-image SR and deblocking for a highly-compressed image on an individual basis activity deblocking and SR. It discussed about deblocking followed by SR, or SR followed by deblocking on an extraordinarily compressed image generally cannot return through a satisfactory visual quality. In our methodology, an image skinny representations for modeling the association between low- and high-resolution image patches in terms of the learned dictionaries for image patches with and whereas not interference artifacts, severally. As a result, image SR and deblocking is at an equivalent time achieved via skinny illustration and morphological half analysis (MCA)-based image decomposition. Experimental results demonstrate the effectualness of the projected algorithm.

S. Lee el at (2015) demonstrate the fast noise-robust interpolation method based on second-order directional-derivatives. It is a challenging work to reproduce the high resolution (HR) image from a noisy low resolution input while preserving its edge structures. In this paper, a fast noise-robust interpolation method is proposed. In the proposed method, the edge information of a pixel to be interpolated is first estimated using a local curvature (LC), which is a second-order directional-derivative obtained from its local neighborhoods. Based on the edge information of the pixel, edge-adaptive interpolation with noise reduction is performed using the proposed LC adaptive filter whose kernel is adaptively determined by comparing the LC values along the two orthogonal directions. A refinement procedure is adopted to further enhance the edge information of the HR image by applying a Laplacian subtraction method using the pre computed LC values. Experimental results show that the proposed method can preserve the edge sharpness while suppressing noise, with low computational complexity.

C. Dong et al (2016) proposed the Image Super-Resolution method of mistreatment Deep Convolutional Networks. This paper deals a deep learning technique for single image super-resolution (SR). Our technique directly learns Associate in nursing end-to-end mapping between the low/high-resolution footage. The mapping is delineate as a deep convolutional neural network (CNN) that takes the low-resolution image as a result of the input and outputs the high-resolution one. We tend to tend to a lot of show that ancient sparse-coding-based SR methods may additionally be viewed as a deep convolutional network. Our deep CNN options a light-weight structure, however demonstrates progressive restoration quality, and achieves fast speed for smart on-line usage. We tend to explore fully totally different network structures and parameter settings to understand trade-offs between performance and speed. An experimental result deals with an ease of an increase our network to handle three color channels at identical time, and show higher overall reconstruction quality.

S. Mandal el at (2017) presented the method of Noise adaptive super-resolution from single image via non-local mean and sparse representation. Our goal is to obtain a noise-free, high resolution (HR) image from an observed low quality noisy low resolution (LR) image. The conventional approach of preprocessing the image with a denoising algorithm, followed by applying a super-resolution (SR) algorithm, has an important limitation. Along with noise, some high frequency content of the image (particularly textural detail) is invariably lost during the denoising step. In this paper, we show that high frequency content in the noisy image (which is ordinarily removed by denoising algorithms) can be effectively used to obtain the missing textural details in the HR domain. To do so, we first obtain HR versions of both the noisy and the denoised images, using a patch-similarity based SR algorithm. We then show that by taking a convex combination of orientation and frequency selective bands of the noisy and the denoised HR images, we can obtain a desired HR image where (i) some of the textural signal lost in the denoising step is effectively recovered in the HR domain, and (ii) additional textures can be easily synthesized by appropriately constraining the parameters of the convex combination. Furthermore, our results show a consistent improvement in numerical metrics, further corroborating the ability of our algorithm to recover lost signal.

Y. Zhao el at (2017) introduced the technique of filtered Mapping-Based Method for Compressed Web Image Super-Resolution. The Web images and videos are often down sampled and compressed to save the bandwidth and storage. Hence, the low-quality and low-resolution Web images/videos cannot match the high-definition display devices nowadays. In this paper, we propose an efficient joint SR and deblocking method based on simple three-step-process, which consists of a block-matching and 3D filtering process, a local binary encoding process, and a mapping reconstruction process. Furthermore, the cascade framework and an extra post-processing are also presented for large magnification factors. Experimental results on real-world Web images with obvious compression artifacts demonstrate that the proposed method can reproduce clear and sharp SR results, and effectively remove the unnatural artifacts at the same time.

III. PROPOSED METHOD

A. *The proposed framework*

In the proposed framework, we merely adopt low-strength filtering to preliminarily reduce obvious blocking artifacts, and then use a learning-based process to jointly recover the SR details and remove remaining artifacts. This framework contains two stages, i.e., the learning stage, in which the mapping functions are computed for different local patches; and the reconstructing stage, in which the LR patches are upsampled by means of the pre-computed mapping functions. Motivated by the efficient local classification based SR framework, we present a simple local encoding to classify the local patches, and then calculate the mapping function via ridge regression. The technical contributions of this paper are summarized as follows, we propose a fast and efficient three-steps-process for joint SR and deblocking, which consists of a BM3D filtering process, a local binary encoding process, and a mapping reconstruction process. Experimental results on real-world web images demonstrate that the proposed method can simultaneously recover clear and sharp SR result and remove noise and blocking artifacts.

In the learning stage, we tend to learn the mapping function for each class of patches by utilizing many known LR/HR image pairs. The LQ and LR images are firstly filtered with slight BM3D filter to reduce obvious compression artifacts. Then the training LR/HR patches are extracted from the filtered images and corresponding HQ and HR images. These training patches are further classified into different classes by means of local encoding process. At last, a mapping function is calculated for each class of local patches.

In reconstructing stage, the input LQ and LR images are also firstly filtered with the same filter. The entire image is then split to local patches with overlapping. For each patch, a binary code is computed as its class-label, and then the corresponding mapping function of that class is directly utilized to magnify the patch. After all the LR patches are reconstructed, the overlapped adjacent patches are averaged to obtain the final HQ and HR image. Fig 3.1 shows the proposed framework.

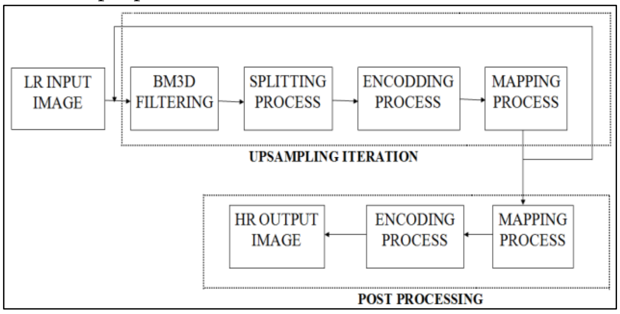

Fig. 3.1: Proposed Framework

B. Filtering

In filtering process, we simply adopt commonly used BM3D filter to preliminarily reduce the compression artifacts. It should be noticed that the proposed method is not a simple stacked pipeline which uses the BM3D to totally remove the artifacts and then applies a learning-based method to magnify the artifacts-free image. Fortunately, the following local encoding and mapping reconstruction can effectively remove the remaining artifacts and reproduce sharp SR results.

C. Local Encoding

The local patch encoding (LPE) is used to characterize the local distribution. However, the 12-bits LPE code and the 17-bits LPE code need 2^{12} (4096) and 2^{17} (131072) kinds of mapping functions, respectively. To achieve accurate local classification with less bit-depth, we propose an effective encoding process based on local binary pattern (LBP) and local binary count (LBC).

We utilize LBP uniform code (LBP^{u2}) to describe the local binary structure. Uniform codes LBPu2 are those LBP codes with U value less than 2 ($U \leq 2$), and all the non-uniform LBP codes are categorized into one same class. In this paper, we use local 3×3 neighbor area ($P=8$), and thus the bit-depth of the LBP^{u2} codes is 6-bits. Comparing to traditional LBP codes, the uniform codes can reduce the bit-depth but provide a vast majority, sometimes over 90%, of the texture surface patterns. The local average gray-value can represent the gray-value level among the entire image. Note that we use the local mean rather than the value of central pixel as in many LBP variants. That is because the single central value is more sensitive to noise, which is often contained in compressed image. Finally, a local patch can be encoded to a 10-bits code by concatenating the 1-bit local average gray-value code, the 3-bits LBC code, and the 6-bits LBP^{u2} code. As a result, the local patches can be classified into 1024 classes by means of the proposed 10-bits encoding, and total 1024 mapping functions are correspondingly computed.

D. Reconstruction with Mapping Function

Given a LR image patch y , the task of image SR is to get its HR patch x , as following,

$$x = f(y)$$

Where $f(\cdot)$ denotes a mapping function from the LR space to HR space. It is very time-consuming to enumerate a mapping function for each patch. By means of the aforementioned local encoding process, different patches can be accurately classified into various classes according to their local distributions. Based on the basic constraint that local patches with same local distribution will also produce similar corresponding HR patches, we can calculate a mapping function for one class instead of each patch. The reconstruction formula is then computed as,

$$x = f^{j}(y), y \in C_j$$

Where Cj is the j -th class of local distributions. For a given LR patch, we can use the proposed encoding process to describe its local distribution. The mapping functions are pre-computed in the learning stage with a training set consisting of many LR/HR patch pairs. Firstly, training samples are classified into different categories according to their 10-bits codes. For an input LR patch y ($y \in C_j$), the samples with same 10-bits codes are used to represent y . Assuming that HR space have a similar local neighbor manifold with LR space, we can use the representation coefficient α in the LR space to estimate the coefficient in the HR space.

IV. EXPERIMENTAL RESULT

A. Training and Testing Image Sets

In this paper, we adopt the commonly used training set proposed by Yang et al. This training set contains 91 natural images collected from the web. For fair comparison, we use two testing sets of Kang's dataset and Ono's dataset. Kang's dataset consists of several real-world web images with significant blocking artifacts. Ono's dataset contains four JPEG compressed gray images.

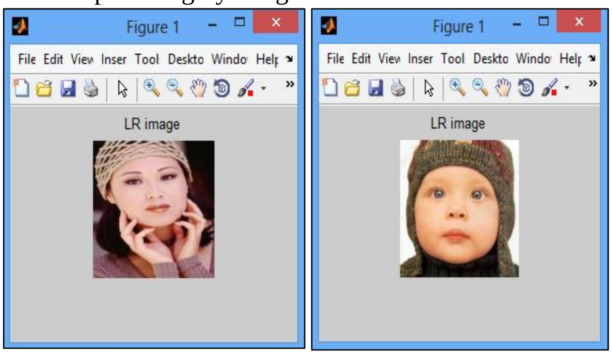

Fig. 4.1: Training LR images

For testing, the LQ and LR images in testing sets are magnified via different methods. For training, we firstly down sample the original HR images to obtain LR images, and then compress these LR images to produce LQ and LR training images. In practice, the quality factor (QF) or codec parameters of web images/frames are often unknown.

B. Filtering Process

The unnatural noise is added to obtain the degraded image quality. Different unnatural noises are available to degrade the image. , the additive white Gaussian noise are added to the LR image to degrade the quality of an image. The resolution of the image can be same as LR image. After the addition of white Gaussian noise, the quality of an images is reduced therefore it can be recovered by filtering the degraded image using weiner Filter.

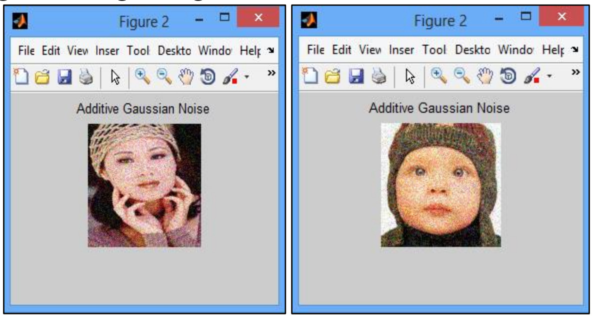

Fig. 4.2: Noisy Images

Fig. 4.3: Filtered images

As illustrated in the Fig4.3, high-strength weiner filtering also known as a block matching filter can recover artifact-free image but also leads to very blurry texture and edges. In order to preserve more high-frequency (HF) information, we only apply low-strength filtering as pre-processing in this paper. As shown in the filtered result in our method still contains lots of unnatural artifacts.

C. Transformation Process

Fortunately, the following local encoding and mapping reconstruction can effectively remove the remaining artifacts and reproduce sharp SR results. After filtering, the splitting process can take place. Here, Discrete Wavelet Transform (DWT) is used to split the image into four patches. The filtered images are classified into four patches by using Haar wavelet transform. Thus, it produces the four bands as LL, LH, HL, and HH.

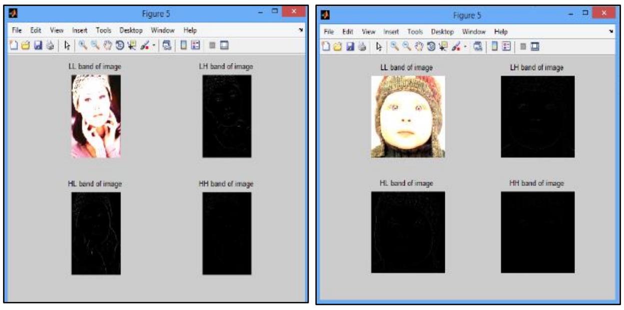

Fig. 4.4: Transformed Images

D. Reconstruction process

The mapping functions are pre-computed in the learning stage with a training set consisting of many LR/HR patch pairs. Firstly, training samples are classified into different categories according to their 10-bits codes. Interpolation refers to the process of finding unknown location using known data points. For different interpolation technique, the resolution values can be varied and the bicubic interpolation provides the better visual quality when compared to other interpolation techniques.

Fig. 4.5: Nearest neighbor, Bilinear and Bicubic Interpolated images

Comparing the results by using different parameters such as SNR, PSNR and MSE values the bicubic interpolation can reproduce the sharp SR images with better visual quality with reasonable computational time.

Data	Interpolation Techniques	SNR (dB)	Time (sec)
Lena image	Nearest	46	1.34
	Bilinear	49	
	Bicubic	59	
Baby image	Nearest	56	1.22
	Bilinear	58	
	Bicubic	65	

Data	Interpolation Techniques	PSNR (dB)	Time (sec)
Lena image	Nearest	42	1.34
	Bilinear	44	
	Bicubic	56	
Baby image	Nearest	50	1.22
	Bilinear	54	
	Bicubic	58	

Data	Interpolation Techniques	MSE (dB)	Time (sec)
Lena image	Nearest	1.24	1.34
	Bilinear	1.05	
	Bicubic	0.21	
Baby image	Nearest	0.6	1.22
	Bilinear	0.3	
	Bicubic	0.14	

From the above tabulations, the various parameters such as MSE, SNR, PSNR and elapsed time values are computed. The comparison between different interpolation techniques are evaluated and finally bicubic interpolation technique was concluded as best method by mathematically when compared with other interpolation techniques.

V. Conclusion

In this paper, we have proposed a fast and high-performance SR method for compressed web images. In the learning stage, we firstly reduce the compression artifacts via BM3D weiner filter. Then we classify different local patches into many classes by means of a local encoding process. An interpolation function from LQ and LR space to HQ and HR space is then computed for each class. In the reconstructing stage, a LR input patch is also filtered and encoded to obtain its local code. Corresponding mapping function is then directly selected to magnify this LR patch. Experimental results on several real-world web images demonstrate that the proposed method can efficiently recover sharp and artifact-free SR results.

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