Review of Super-Resolution Image Reconstruction and Comparision of Super Resolution Methods

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ABSTRACT

Images are often down sampled and transmitted at low bit rates resulting in a low resolution(LR) compressed image, due to the factors like processing power limitations and channel capabilities. High resolution(HR) images can be reconstructed from several blurred, noisy and down sampled low resolution images using a computational process know as super resolution(SR) image reconstruction. In this paper, We are going to review what are the problem with current image capturing techniques and how SR technique helps to solve those problem. We have reviewed its applications and basic methods used for SR image reconstruction, we have compare all these methods as well and at the end of paper we have given advance issues in SR with some recent work in SR.

Keywords: *Resolution, Restoration, Wavelet lifting scheme*

I. INTRODUCTION

In most electronic imaging applications, images with HR are desired and often required.HR means that pixel density within an image is high, therefore an HR image can offer more details in various applications. Charge-coupled device (CCD) and CMOS image sensors are suitable for most imaging applications but the current resolution level and product price will not satisfy the future demand. Thus, finding a new way to increase the current resolution level is needed.

The most common solution to increase spatial resolution is to reduce the pixel size (i.e., increase the number of pixels per unit area) by sensor manufacturing techniques. If the pixel size decreases, the amount of light available also decreases. It generates shot noise that degrades the image quality severely. Second approach for enhancing the spatial resolution is to increase the chip size, which leads to an increase in capacitance [1]. Since large capacitance makes it difficult to speed up a charge transfer rate, So this approach is not considered effective. The high cost for high precision optics and image sensors is also an important concern in many commercial applications regarding HR imaging.

Solution to above problem and one promising approach is to use signal processing techniques to obtain an HR image from observed multiple LR images.

This paper is organized as follows. In Section II, We describe the introduce the Super Resolution and its Applications; Section III provides SR Image Reconstruction Methods. In section IV We describe Advanced Issues in SR and recent work, Section V provides conclusion and finally in section VI consists of future Work.

II. INTRODUCTION OF SR AND IT'S APPLICATIONS

In SR techniques, The basic premise for increasing the spatial resolution is the availability of multiple LR images captured from the same scene [4]. In SR, typically, the LR images represent different "looks" at the same scene. That is, LR images are sub sampled (aliased) as well as shifted with sub pixel precision. If the LR images are shifted by integer units, then each image contains the same information, and thus there is no new information that can be used to reconstruct an HR image. If the LR images have different sub pixel shifts from each other and if aliasing is present, then each image cannot be obtained from the others. Here new information contained in each LR image can be exploited to obtain an HR image. if we combine these LR images, SR image reconstruction is possible.

There is a natural loss of spatial resolution caused by the optical distortions due to out of focus, diffraction limit, etc., motion blur due to limited shutter speed, noise that occurs within the sensor or during transmission, and insufficient sensor density in the process of recording a digital image.

A related problem to SR techniques is image restoration, which is a well-established area in image processing applications [5]. The goal of image restoration is to recover a degraded (e.g., blurred, noisy) image, but it does not change the size of image. Actually, restoration and SR reconstruction are closely related theoretically and SR reconstruction can be considered as a second-generation problem of image restoration. One more problem related to SR reconstruction is image interpolation that has been used to increase the size of a single image.

Most papers on SR implementations provide subjective results by comparing the SR image to a bilinear interpolated image or the source HR image from which the LR images were created. This provides neither a clear method of comparing different SR methods nor a way of demonstrating a particular SR methods suitability for a desired application. Comparisons between various SR techniques have been primarily concerned with what assumptions are made in modeling the SR problem. Some of these assumptions include assuming the blurring process to be known [3] or that regions of interest among multiple frames are related through global parametric transformations [2]. Other models take into account arbitrary sampling lattices, a digital sensor elements physical dimensions, a non-zero aperture time, focus blurring, and more advanced additive noise models. Many times these assumptions are chosen to simplify a model and are usually biased toward a particular method. Methods employing models with fewer restrictions are assumed to have higher performance. However, methods that do not make these assumptions have not demonstrated objectively that removing these assumptions yields better SR reconstruction performance. Signal-to-noise ratio, peak signal-to noise ratio (PSNR), root mean squared error, mean absolute error, and mean square error (MSE) of super-resolved images versus interpolated images have all been used as objective measures of SR accuracy; however, the prominent method of presenting results in literature has clearly been subjective visual quality.

The SR image reconstruction is proved to be very useful in many practical cases where multiple frames of the same scene can be obtained. It includes video applications, medical imaging and satellite imaging. Other application is to reconstruct a higher quality digital images from LR images obtained with an inexpensive LR camera/camcorder for printing or frame freeze purposes. Typically, with a camcorder, it is also possible to display enlarged frames successively. Synthetic zooming of region of interest (ROI) is another important application in surveillance, forensic, scientific, medical, and satellite imaging.

III. METHODS OF SR

There are many existing SR methods including non-uniform interpolation, frequency domain, deterministic and stochastic regularization, projection onto convex sets (POCS), hybrid techniques, optical flow, and other approaches [3][2][8]. Additionally several methods provide parameters that can effect tradeoffs between such factors as fidelity and smoothness or quality and computation time.

Non-uniform Interpolation

The basis of non-uniform interpolation SR techniques is the non-uniform sampling theory which allows for the reconstruction of functions from samples taken at non-uniformly distributed locations. This was developed by Clark et al. [9] and later extended to two-dimensional signals by Kim and Bose [10]. SR image enhancement is a logical application of this new theory, but one that requires very accurate registration between images. Non-uniform interpolation is a basic and intuitive method of super-resolution and has relatively low computational complexity, but it assumes that the blur and noise characteristics are identical across all LR images [3].

Frequency Domain

Tsai and Huang [6] proved that in the absence of noise or blurring it is possible to reconstruct a HR image from multiple LR images based on the aliasing present in the LR images. This was accomplished by relating the aliased discrete fourier transform coefficients of the LR images to a sampled continuous fourier transform of an unknown HR image. Kim and Bose extended this to blurred and noisy LR images, provided the noise has zero mean and the blur and noise are identical across all LR images, using a recursive implementation based on the weighted least square theory [10].

Regularization

SR image reconstruction is generally an ill posed problem. However, it can be stabilized with a regularization procedure. Without loss of generality, we can define a model to relate LR images with the original HR image and additive noise as:

$$Y_k = W_k X + n_k \; for \; k = | 1, \ldots, p$$

By assuming that registration parameters are estimated, the inverse problem can be solved by deterministic regularization by taking proper prior information about the solution. For example, a constrained least square (CLS) method can be used to find x such that

$$\left[\sum_{k=1}^{p} \| y_k - W_k x \|^2 + \alpha \| C x \|^2 \right]$$

becomes minimum. In this method a smoothness constraint is used as priori knowledge for reconstruction. Parameter α, which is known as the regularization parameter, controls the trade off between fidelity and smoothness in the solution. Current research is focused on simultaneous blur identification and robust super-resolution.

Projection Onto Convex Sets

Low resolution images usually suffer from blurring caused by a sensor’s point spread function (PSF) and additionally from aliasing caused by under-sampling. Stark and Oskoui [12] have proposed a POCS technique that accounts for both the blurring introduced by the sensors as well as the effects of undersampling. In their model a low resolution image sequence is denoted by g(m1,m2, k). It is assumed that an estimate of the high resolution image at time k = tr is desired. A family of closed, convex constraint sets can be defined, one for each pixel within the low-resolution image sequence

$$C_{t_r}(m_1, m_2, k) = \{ y(n_1, n_2, t_r) : | r^{(y)}(m_1, m_2, k) | \leq \delta_0 \}$$

$$r^{(y)}(m_1, m_2, k) \dot{=} g(m_1, m_2, k) - \sum_{(n_1, n_2)} y(n_1, n_2, t_r) h_{t_r}(n_1, n_2; m_1, m_2, k)$$

is the residual associated with an arbitrary member, y, of the constraint set. htr combines the effect of the blur PSF and relative motion of object and sensor. The quantity _0 is an a priori bound reflecting the statistical confidence with which the actual image, y, is a member of the set Ctr (m1,m2, k) This family of constraints is referred to as data consistency constraints. An estimate of the high-resolution version of the reference image is determined iteratively starting from some arbitrary initialization. Successive iterations are obtained by projecting the previous estimate onto the consistency set with an amplitude constraint set that restricts the gray levels of the estimate to the range [0, 255].

Optical Flow

Some applications can benefit from the generalization of SR techniques to support the imaging of objects that are non-planar, non-rigid, or which are subject to self-occlusion when rotated. One such application is SR reconstruction of facial images. Baker and Kande present optical flow as a solution to this problem [13]. Zhao and Sawhney present a comparison of three different flow methods: least-squares based flow, consistent flow (CONS), and bundled flow with CONS flow as initial input. They demonstrated that it worked well when small amount of noise were present, but that it was very sensitive to flow accuracy [2].

Results for the Lena Image both MSE and PSNR show the Vandewalle et al. method is significantly improved over the other SR images. The MSSIM measure in this case is the only quality measurement that favors the Irani-Peleg SR image. Our informal subjective assessment of the images also favors the Irani-Peleg image.

The Mandrill image has more pronounced high frequency detail. The LCAV method does a particularly good job recovering details such as the whiskers of the mandrill. Not surprisingly Vandewalle et al. was favored by all three objective measurements. However, the Kim et al. method again performed worse in both MSE and PSNR measures than the bilinear interpolated image, while visually (and in MSSIM) it is clear that Kim et al. provides a much better image.

LENA

Method	**Complexity**		**Quality Measurements**		
	Itterative	**Relative Complexity**	**MSE**	**PSNR**	**MSSIM**
Kim et al. [10] [14]	Yes	Medium	0.0087725	20.569	0.66687
Irani-Peleg [15] [16]	Yes	Medium	0.0044577	23.509	0.81647
Wavelet [17] [18]	Yes	High	0.0063555	21.969	0.68759
Vandewalle et al. [3][19]	Yes	Low	0.0021182	26.74	0.81441
Bilinear Interpolation		Negligable	0.0061053	22.143	0.67013


HR Lena


Bilinear Upsampled


Kim et al.


Irani-Peleg


Harr Wavelet


Vandewalle et al.

MANDRILL

Method	**Complexity**		**Quality Measurements**		
	Itterative	**Relative Complexity**	**MSE**	**PSNR**	**MSSIM**
Kim et al. [10] [14]	Yes	Medium	0.014926	18.261	0.52432
Irani-Peleg [15] [16]	Yes	Medium	0.011321	19.461	0.54386
Wavelet [17] [18]	Yes	High	0.012211	19.133	0.52639
Vandewalle et al. [3][19]	Yes	Low	0.008321	20.798	0.68132
Bilinear Interpolation		Negligable	0.012956	18.875	0.4256


HR Mandrill


Bilinear Upsampled

Kim et al.

Irani-Peleg

Harr Wavelet

Vandewalle et al.

IV. ADVANCED ISSUES IN SR AND RECENT WORK

We present the advanced issues which are important open problems within the SR area.

SR Considering Registration Error

Registration is a very important step to the success of the SR image reconstruction as mentioned earlier. Therefore, accurate registration methods, based on robust motion models including multiple object motion, occlusions, transparency, etc., should be needed.

Blind SR Image Reconstruction

In many practical situations the blurring process is generally unknown or is known only to within a set of parameters. So, it is necessary to incorporate the blur identification into the reconstruction procedure.

Computationally Efficient SR Algorithm

To apply the SR algorithm to practical situations, it is important to develop an efficient algorithm that reduces the computational cost.

A PDE Approach to Super-resolution with Contrast Enhancement[20]

Here, They present a fast partial differential equation (PDE) model for multi-frame image super resolution reconstruction. Then combine their proposed super resolution model with the local histogram equalization (LHE), which perform super resolution and enhance image contrast simultaneously. It overcomes the shortcomings of recent promising super resolution methods dealt with super resolution and contrast enhancement separately.

A High-efficiency Super-resolution Reconstruction Algorithm from Image/Video Sequences[21]

So far, existing super-resolution reconstruction methods are all confronted with the problem of slow convergence and expensive computation. To satisfy the requirement of real-time application, They propose a high-efficiency super-resolution reconstruction algorithm that solves two key bottlenecks in the multi-frame MAP framework. The first breakthrough is to select the Armijo rule to identify the step length instead of the exact line search. The second one is to approximately compute the gradient of the MAP objective function using analytic representation instead of numerical calculation.

Super Resolution Reconstruction of Compressed Low Resolution Images using Wavelet Lifting Schemes[22]

Here, They propose lifting schemes for intentionally introducing down sampling of the high resolution image sequence before compression and then utilize super resolution techniques for generating a high resolution image at the decoder. Lifting wavelet transform has its advantages over the ordinary wavelet transform by way of reduction in memory required for its implementation. This is possible because lifting transform uses in-place computation. The lifting coefficients replace the image samples present in the respective memory locations.

V. CONCLUSION

In this paper we tried to address the concept of SR technology by providing an overview of existing SR methods and advanced issues currently under investigation. Some other issues in the SR techniques to improve their performance are currently focused on the color SR algorithm and the application to compression systems. It is necessary to extend the current SR algorithm to a real-world color imaging system.

SR image reconstruction is one of the most spotlighted research areas because of its practical applications and it can overcome the inherent resolution limitation of the imaging system and improve the performance of most digital image processing applications.

VI. FUTURE WORK

We would like to further explore the Wavelet method[21][7] and in that we would like to see impact of different scaling factors and wavelet filters for possible image sharpening and enhancement and we would also want to merge contrast enhancement technique given in[20] with wavelet method in our future studies.

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