Superresolution: A Novel Application to Image Restoration

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***Abstract*—The subject of extracting particular high-resolution data from low-resolution images is one of the most important digital image processing applications in recent years, attracting much research. This paper shows how to improve the resolution of real images when given image is in the degraded form. In the superresolution restoration problem, an improved resolution image is restored from several geometrically warped, blurred, and noisy and downsampled measured images. To obtain this result the use an iterative nonlinear restoration blind deconvolution maximum likely-hood algorithm imposing the low frequencies complete data of the original low-resolution image and the high-resolution data present only in a fraction of the image which suppresses the noise amplification and avoid the ringing in deblurred image. Our results show that a high resolution real image derived from superresolution methods enhance spatial resolution and provides substantially more image details.**

Index Terms- Image Processing, Super-resolution,

I. Introduction

Cambridge International Advanced Learner's dictionary defines 'Superresolution' as 'the ability of a microscope, or a television or computer screen, to show things clearly and with a lot of detail:'

Superresolution refers to the reconstruction methods that can be applied to obtain an image with higher spatial resolution through the use of several lower-resolution (LR) images.

The main objective is to achieve the best image quality possible from several LR images. However, not all LR images are useful for SR. The application of SR algorithms is possible only if aliases exist, and the images have sub-pixel shifts. There are many different SR techniques and they can be applied in the frequency domain or the spatial domain. However, the latter provides better flexibility in modeling noise and degradation; we focus our analysis in the spatial domain.

Whenever dynamic image enhancement is needed, such as on some web pages, super-resolution techniques can be utilized. This paper focuses on the issue of how to increase the resolution of a single image using only prior information about images in general, and not relying on a specific training set or the use of multiple images.

The methods for achieving super-resolution are as varied as the applications. They range from simple use of Gaussian or preferably median filtering, to supervised learning methods based on learning image patches corresponding to low resolution regions from training data. This paper use an approach of an iterative nonlinear restoration procedure using the Lucky-Richardson algorithm imposing to the low frequencies complete data of the original low-resolution image and the high-resolution data present only in a fraction of the image.

The objective is to further our understanding of a high resolution medical image derived from conventional SR methods. Quantitative indices as well as visual assessments are used to evaluate the SR image results.

SR refers to recovering high resolution data from images that due to mis-focus, compression or other forms of distortion have lost the data that were originally embedded in the higher frequencies of the image, and hence are now given as low resolution images. The methods to overcome this problem of data loss, and generate SR, are quite versatile.

II. Problem Setup

Camera shake, in which an unsteady camera causes blurry photographs, is a chronic problem for photographers. Many photographs capture ephemeral moments that cannot be recaptured under controlled conditions or repeated with different camera settings. If camera shake occurs in the image for any reason, then that moment is "lost".

In some cases the method is to obtain data concerning the blurring function and use an inverse filter to reconstruct the high-resolution image [1,2]. Unfortunately, two main problems limit this approach. The first, usually it is impossible to identify the exact blurring function since it is a result of stochastic noise and thus only its statistical properties are known.

The second problem is that, even if the blurring function is known making an inverse filter might not be practical (e.g. if the original blurring filter has zeros the inverse filter must have singular values to obtain exact restoration). Other methods use large databases; they are divided into two groups. In the first group [3, 4] one takes a large amount of different test-images present both in a low resolution version and a high resolution version, and attempt to find the blurring procedure that will yield the best results with respect to all images. There are two problems with this approach, no two pictures are identical and therefore we cannot be sure that the inverse blurring procedure found will be applicable for the required new image, and, usually the blurring procedure varies from one test-image to another and thus the “anti-blurring” filter will not be an exact filter.

The second group of SR using large databases assumes one has many low-resolution pictures of the required subject [5, 6]. Since in every picture a different portion of the high-resolution data is missing it is possible to extract some high-resolution data from these images to obtain a single high-resolution image. The main drawback of these methods is the large database required in order to increase the resolution of a single image.

In our work we suggest a novel approach assuming only one image is given – the required image. In the CT scan process, only the abnormality in the patient’s brain is scanned at peak resolution and most of the part scanned with lower accuracy, the process itself will become much faster and the storage capacity required to store the images will become much smaller reducing the patient’s inconvenience on the scanning device. This is the exact principle used in this work. We extract only a required small portion of the image which is available in high- resolution and use this extracted data having similar statistical properties to the neighboring low-resolution portion of the image to increase the resolution of the entire image.

To do this, we use an iterative procedure relying on two initial assumptions: in one small portion of the image we have all the high-resolution data, and the entire image contains all the low frequencies of the original high-resolution image. In the following sections we explain the procedure and show some test cases supporting this approach.

Every user of multimedia technology expects good image and video visual quality independently of the particular characteristics of the receiver or the communication networks employed. Unfortunately, due to factors like processing power limitations and channel capabilities, images or video sequences are often downsampled and/or transmitted or stored at low bit rates, resulting in a degradation of their final visual quality.

This paper introduces a new technique for removing the effects of unknown camera shake from an image. This advance results from two key improvements over previous work. First, we exploit recent research in natural image statistics, which shows that photographs of natural scenes typically obey very specific distributions of image gradients. Second, we build on work by Miskin and MacKay [2000], adopting a Bayesian approach that takes into account uncertainties in the unknowns, allowing us to find the blur kernel implied by a distribution of probable images. Given this kernel, the image is then reconstructed using a standard deconvolution algorithm, although we believe there is room for substantial improvement in this reconstruction phase.

We further assume that each of the measured images is contaminated by non-homogeneous additive Gaussian noise, uncorrelated between different measurements. Fig. 1 illustrates the image degradation model. In order to treat the most general case, it is assumed that each measurement is the result of different blur, noise, motion, and decimation parameters. Translating the above description to an analytical model, we get

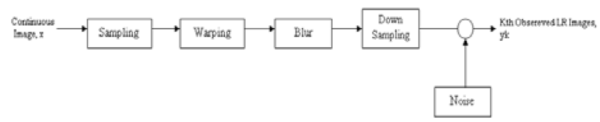


Fig. 1: Degradation Model.

$$y_k = DB_k M_k x + n_k \, for 1 \le k \le p \qquad (1)$$

The geometric warp matrix M_k is a one-to-one representation of the optic flow between the *nondecimated noiseless* version of the *kth* measured image and the ideal image x.

The assumption on the *a priori* knowledge of the blurring matrix, B_k can be explained in some applications by referring the blur to measurable phenomena, such as optics and sensor blur. In other cases, we may assume that the superresolution restoration process is robust to errors in the blurring function.

The decimation ratio between the ideal image and the *kth* measurement image can only be determined by parameter matrix D . This ratio is directly drawn from the ratio between the number of pixels in the measured image $[N_k \times N_k]$ and the ideal image $[L \times L]$ .The above restoration problem can be formulated in terms of the following equation

$$y_k = H \cdot x + n_k \, for 1 \le k \le p \; . \qquad (2)$$

Where, $H = DB_k M_k$.

III. Super-resolution Restoration Process

Super-resolution technique is typically used to restore a high resolution image from several interpolated low-resolution noisy observations.

Super-resolution restoration is an example of an ill-posed inverse problem. Such problems may be tackled by constraining the solution space according to a-priori knowledge of the form of the solution (smoothness, positivity etc.). Super-resolution restoration is critically dependent on accurate, sub-pixel motion estimation.

Inclusion of such constraints is essential for achieving high quality of image restoration.

Super-resolution restoration methods may be categorized into two main divisions -frequency domain and spatial domain techniques.

TABLE I.
COMPARISON OF FREQUENCY DOMAIN AND SPATIAL DOMAIN

	Frequency Domain	**Spatial Domain**
Observation Model	Frequency Domain	Spatial Domain
Motion Models	Global Translation	Almost unlimited
Degradation Models	Limited, LSI	LSI or LSV
Noise Model	Limited, SI	Very Flexible
SR Mechanism	De-aliasing	De-aliasing a-priori info
Computational Requirements	Low	High
A-priori info	Limited	Almost unlimited
Regularization	Limited	Excellent
Extensibility	Poor	Excellent
Applicability	Limited	Wide
Application Performance	Good	Good

In the early stages, most of the research work is carried out under frequency domain approach but as more general degradation models were considered, later research has tended to concentrate almost exclusively on spatial domain formulations.

Generally, bilinear or bicubic interpolation process are mostly used for the low resolution image enhancement in superresolution technique. The solution to the above discussed problem can be illustrated form fig. 2.

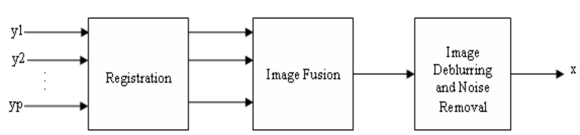


Fig. 2 : Restoration process for Superresolution.

Basically, superresolution technique for images is carried out along with three stages successively- image registration, image fusion and image deblurring.

Image registration is the task of finding the geometric transformation between two or more views of the same scene (i.e. set of LR images y_1, y_2, …..y_p). In its most generalized form, a unique correspondence is found between every point in one image to another point in a second image; both points represent the same physical point in the scene.

The term fusion means in general an approach to extraction of information acquired in several domains. The goal of image fusion (IF) is to integrate complementary multisensor, multitemporal and/or multiview information into one new image containing information the quality of which cannot be achieved otherwise. Images of the same scene are acquired at different time instances either to find and evaluate changes in the scene or to obtain a less degraded image of the scene. The former aim is common in medical imaging, especially in change detection of organs and tumors, and in remote sensing for monitoring land or forest exploitation. Numerous fusion applications have appeared in medical imaging like simultaneous evaluation of CT, MRI, and/or PET images. Plenty of applications which use multisensor fusion of visible and infrared images have appeared in military, security, and surveillance areas.

In the image deblurring process, although image fusion already achieves some SR by unwrapping the aliased frequencies of the LR images, the resulting spectrum power is significantly attenuated by optical blur, motion blur and sensor integration.

Usually, to solve the eq. 2, we must have a set of LR images in order for restoration process. But it is some what difficult task to determine the set of LR images, so the novel procedure of stochastic approach of MAP regularization technique is mostly helpful in such case.

According to the MAP estimator, the additive noise, the measurements, and the ideal image are all assumed stochastic signals. The MAP estimation of the unknown image X is done by maximizing the conditional probability density function of the ideal image given the measurements $P\{X/Y\}$. Based on Bayes rule, maximizing $P\{X/Y\}$ is equivalent to maximizing the function $P\{Y/X\}P\{X\}$ .Bayesian approach provides a flexible and convenient way to model a priori knowledge concerning solution

$$X = \arg\max P(x|y_1, y_2, \ldots\ldots\ldots, y_p)$$

$$X = \arg\max \{\ln P(x|y_1, y_2, \ldots\ldots\ldots, y_p) + \ln P(X)\}$$

The mathematical operation shows the final result as:

$$R = \hat{X} \cdot P$$

Where, $R = Q^{-1} + \sum_{k=1}^{p} H_k^T W_k H_k$ and

$$P = \sum_{k=1}^{p} H_k^T W_k Y_k$$

If we assume that the measurements additive noise is zero mean Gaussian random process with autocorrelation matrix W with autocorrelation matrix Q for unique estimate image $\hat{X}$ using iterative technique.

Image restoration is the inverse process of degradation which can be given by the following relation

$$g\,(x, y) = H\,.[f\,(x, y)] + \eta\,(x, y) \qquad (3)$$

Eq.(3), shows the model of image degradation or restoration process together with additive noise term, operates on an input image f (x, y) to produce a degraded image g (x, y). Given g (x, y), some knowledge about the degradation function H which gives the quality of blurred or degraded image and some knowledge about the additive noise term η (x, y), the objective of restoration is to obtain an estimate $\hat{f}(x, y)$, of the original image.

If H is a linear, spatially invariant process, it can be shown that the degradation image is given in spatial domain by

$$g\,(x, y) = h(x, y) * f\,(x, y) + \eta\,(x, y) \qquad (4)$$

where, h(x, y) is the spatial representation of the degradation function and '* ' indicates the convolution.

In spatial domain, h(x, y) is known as point spread function (PSF), a term that arises from letting h(x, y) operates on a point of light to obtain the characteristics of the degradation for any type of input.

The Blind Deconvolution Algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The algorithm restores the image and the point-spread function (PSF) simultaneously. The blurred and noisy image is restored by the iterative, accelerated, damped Lucy-Richardson algorithm. The Richardson-Lucy method (Richardson 1972, Lucy 1974, Shepp &Vardi 1982) was developed specifically for data comprising discrete, countable events that follow a Poisson distribution. The algorithm maximizes the likelihood that the resulting image, when convolved with the PSF, is an instance of the blurred image, assuming Poisson noise statistics.. The nonlinear maximum -likelihood function is minimized iteratively using multiplicative corrections:

$$\hat{f}_{k+1}(x, y) = \hat{f}_k(x, y)\left[h(-x,-y) * \frac{g(x, y)}{h(x, y) * \hat{f}(x, y)}\right] \qquad (5)$$

In Eq. (5), "*" indicates the convolution, $\hat{f}$ is the estimate of the degraded image and g and h are defined in eq.(3).

In addition, this algorithm demands a manageable amount of computer time and the restored images are robust against small errors in the PSF. However, the main drawback of the Lucy-Richardson algorithm is that it may have a noise amplification problem. This problem is common for the maximum likelihood techniques that attempt to fit the data as closely as possible. If the degraded image is very noisy, trying to fit the noise too closely with many iterations, may result in a restored image with speckled appearance. To cope with this difficulty, the usual approach is to stop the iteration when the restored image seems to be too noisy.

In the frequency domain, degradation model can be depicted from eq. (4) as

$$G\,(u, v) = F\,(u, v).H\,(u, v) + N\,(u, v) \qquad (6)$$

If the noise component is assumed to be negligible or zero and PSF is known then, eq. (6) can be termed as

$$F(u,v) = \frac{G(u,v)}{H(u,v)} \qquad (7)$$

Obtaining the corresponding estimate of the image by taking the inverse Fourier transform of $\hat{F}(u,v)$ which is known as inverse filtering and can be given by following term

$$\hat{f}(u,v) = F^{-1}\left[\frac{G(u,v)}{H(u,v)}\right] \qquad (8)$$

Restoration of image with some knowledge of $H(u,v)$ along with some noise component *which* is considered as a filter

$$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)} + \frac{N(u,v)}{H(u,v)} \qquad (9)$$

If one compare the above equation with eq. (7), only the factor $N(u,v)$ and $H(u,v)$ differentiate from the $F(u,v)$ with $\hat{F}(u,v)$ because noise component is random function whose Fourier transform $N(u,v)$ is not known. In addition there is usually is a problem in practice with function $H(u,v)$ having numerous zeros. The key idea in order to minimize this factor is that the zeros in $H(u,v)$ are less likely to occur near the origin because the magnitude of the transform typically is at its highest value in that region.

By considering the stochastic least mean square filtering operation in order to minimize the error function as

$$e^2 = \min E\left\{\left[f(x,y) - \hat{f}(x,y)\right]^2\right\} \qquad (10)$$

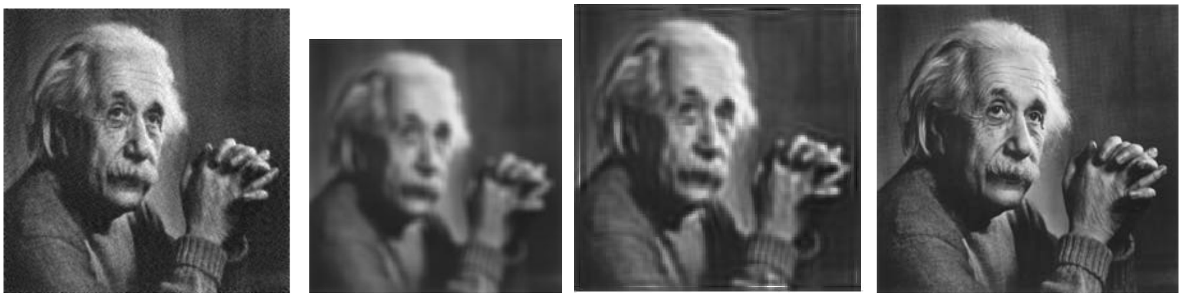
The solution can be achieved through following expression

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)}\frac{|H(u,v)|^2}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right]G(u,v) \qquad (11)$$

Where, the ratio $S_\eta(u,v)/S_f(u,v)$ is called the *noise-to-signal* power ratio. For inverse filtering action it is equal to zero and $|H(u,v)|^2$ is the product of complex conjugate of $H(u,v)$ and self $H(u,v)$.

IV. Experimental Analysis.

The blind deconvolution algorithm maximizes the likelihood that the resulting image, when convolved with the resulting PSF, is an instance of the blurred image, assuming Poisson noise statistics.



(a) (b) (c) (d)

Fig. 3 The Great Scientist- Albert Einstein. (a) Original image, (b) Blurred, Noisy, Downsampled LR image [200 200], (c) Recovered Image with ringing with 100 iterations, (d) Recovered bicubic Interpolated SR image [800 800].

An Approach to blind deconvolution that has received significantly attention over the past two decades which is based on the maximum –likelihood estimation (MLE) an optimization strategy used for obtaining estimates of qualities corrupted by random noise.

The blind deconvolution algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The *deconvblind* function available in MATLAB, Image Processing Toolbox can restore the image and the PSF simultaneously, using an iterative process similar to the accelerated, damped Lucy-Richardson algorithm. The *deconvblind* function implements several adaptations to the original Lucy-Richardson maximum likelihood algorithm that address complex image restoration tasks. Using these adaptations, one can reduce the effect of noise on the restoration, account for nonuniform image quality (e.g., bad pixels) and can handle camera read-out noise.

Also this function supports PSF constraints that can be passed in through a user-specified function. In a real application, you might need to return *deconvblind*, experimenting with PSFs of different sizes, until you achieve a satisfactory result. The restored PSF returned by each deconvolution can also provide valuable hints at the optimal PSF size.

We start with a single high quality image as shown in Fig. 3, from which we can get the exact idea for enhancement of superresolution processing. Fig. 3(b) shows the degradation of image in terms of blurred, gaussian noisy and downsampled low resolution [200 200] image.

Ringing effect observed in fig. 3(c) can greatly be suppressed by specifying weighting function. The algorithm weights each pixel according to the *WEIGHT* array while restoring the image and the PSF. In our example, we start by finding the "sharp" pixels using the edge function. By trial and error, we determine that a desirable threshold level is 0.5.The image is restored by calling *deconvblind* with the *WEIGHT* array and an increased number of iterations -100. Almost all the ringing is suppressed.

Fig. 3(d) shows the final recovered bicubic upsampled HR image [800 800].

V. Application

Nowadays, in order to quench the thirst of recent multimedia technologies, image superresolution techniques is on great demand which include the following various application.

A. Medical imaging

The SR technique is also useful in medical imaging such as computed tomography (CT) and magnetic resonance imaging (MRI) since the acquisition of multiple images is possible while the resolution quality is limited. The surgeon can operate more successfully over the exact fractured part of the body with more care.

B. Satellite imaging

In satellite imaging applications such as remote sensing, several images of the same area are usually provided, and the SR technique to improve the resolution of the target image can be considered. Multispectral image restoration can be carried out over the multispectral bands of satellite imagery in order to improve the resolution of the captured satellite images through low cost satellite sustem.

C. Mobile camera images

A mobile camera images are generally very low in resolution so, to enhance the HR of the mobile camera images the proposed technique is very much useful.

The proposed technique can also be very much useful or enhancing the images captured by low cost and low configuration digital cameras.

D. Video applications

In video application, the motion blur estimation can be performed in order to improve the video resolution of the real time video image processing applications by following spatial domain analysis.

VI. Conclusion And Future Scope

Superresolution techniques show all the reality in detail with regards to that image. We demonstrate that there is an ability to restore an image with improved resolution, based on several motionless blurred, decimated, and noisy images. This paper presented a SR method which proved to be meaningful for cases when an insufficient number of input LR images are available to perform SR with only integer factors, such as two or three.

Work is also in progress in order to extract the Content based image Retrieval (CBIR) pattern for biomedical images, satellite images and historical images. Also in future scope, this algorithm can be very useful for the real time video image processing by improving the live feature extraction parameters.

The proposed technique can enhance the future of the multimedia digital image processing by means of super resolution. Through this technique one can achieve the measurable quantity and quality of high image resolution without using much costlier digital cameras.

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