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A Novel method for Unified Blind motion Deblurring of single / multi image / video Using Blur Deconvolution

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Abstract: **This paper presents, for the first time, a unified blind method for multi-image super-resolution (MISR or SR), single-image blur deconvolution (SIBD), and multi-image blur deconvolution (MIBD) of low-resolution (LR) images degraded by linear space-invariant (LSI) blur, aliasing, and additive white Gaussian noise (AWGN). The proposed approach is based on alternating minimization (AM) of a new cost function with respect to the unknown high-resolution (HR) image and blurs. The regularization term for the HR image is based upon the Huber-Markov random field (HMRF) model, which is a type of variational integral that exploits the piecewise smooth nature of the HR image. The blur estimation process is supported by an edge-emphasizing smoothing operation, which improves the quality of blur estimates by enhancing strong soft edges toward step edges, while filtering out weak structures. The parameters are updated gradually so that the number of salient edges used for blur estimation increases at each iteration. For better performance, the blur estimation is done in the filter domain rather than the pixel domain, i.e., using the gradients of the LR and HR images. The regularization term for the blur is Gaussian (L2 norm), which allows for fast noniterative optimization in the frequency domain. We accelerate the processing time of SR reconstruction by separating the upsampling and registration processes from the optimization procedure. Simulation results on both synthetic and real-life images (from a novel computational imager) confirm the robustness and effectiveness of the proposed method.**

Keywords: **Blur Decovolution, High Resolution, Edge Emphasizing, Blur Estimation, Filtering Domain.**

I. INTRODUCTION

Capturing high-quality images and videos is critical in many applications such as medical imaging, astronomy, surveillance, and remote sensing. Traditional high-resolution (HR) imaging systems require high-cost and bulky optical elements whose physical sizes dictate the light-gathering capability and the resolving power of the imaging system, a constraint that has persisted since their invention. In contrast, computational imaging systems combine the power of digital processing with data gathered from optical elements to generate HR images. Artifacts such as aliasing, blurring, and noise may affect the spatial resolution of an imaging system, which is defined as the finest detail that can be visually resolved in the captured images.

Blur deconvolution (BD) and super-resolution (SR) are two groups of techniques to increase the apparent resolution of the imaging system. One major difference between these two groups is that the goal in a BD problem is just to undo blurring and noise, whereas SR also removes or reduces the effect of aliasing. As a result, the input and output images in BD are of the same size, while in SR the output image is larger than the input image(s). The other difference is that since severe blurs eliminate or attenuate aliasing in the underlying low-resolution (LR) images, the blur in a SR problem may not be as extensive as in a BD problem.

Superresolution (SR) is a class of techniques that enhance the resolution of an imaging system. In some SR techniques—termed *optical* SR—the diffraction limit of systems is transcended, while in others—*geometrical* SR—the resolution of digital imaging sensors is enhanced.

In mathematics, **deconvolution** is an algorithm-based process used to reverse the effects of convolution on recorded data. The concept of deconvolution is widely used in the techniques of signal processing and image processing. Because these techniques are in turn widely used in many scientific and engineering disciplines, deconvolution finds many applications.

In general, the object of deconvolution is to find the solution of a convolution equation of the form:

$$f * g = h$$

Usually, h is some recorded signal, and f is some signal that we wish to recover, but has been convolved with some other signal g before we recorded it. The function g might represent the transfer function of an instrument or a driving force that was applied to a physical system. If we know g, or at least know the form of g, then we can perform deterministic deconvolution. However, if we do not know g in advance, then we need to estimate it. This is most often done using methods of statistical estimation.

In physical measurements, the situation is usually closer to

$$(f * g) + \varepsilon = h$$

In this case ε is noise that has entered our recorded signal. If we assume that a noisy signal or image is noiseless when we try to make a statistical estimate of g, our estimate will be incorrect. In turn, our estimate of f will also be incorrect. The lower the signal-to-noise ratio, the worse our estimate of the deconvolved signal will be. That is the reason why inverse filtering the signal is usually not a good solution. However, if we have at least some knowledge of the type of noise in the data (for example, white noise), we may be able to improve the estimate of f through techniques such as Wiener deconvolution.

The foundations for deconvolution and time-series analysis were largely laid by Norbert Wiener of the Massachusetts Institute of Technology in his book *Extrapolation, Interpolation, and Smoothing of Stationary Time Series* (1949). The book was based on work Wiener had done during World War II but that had been classified at the time. Some of the early attempts to apply these theories were in the fields of weather forecasting and economics.

II. LITERATURE SURVEY

EXISTING SYSTEM

[1] Adaptive flat multiresolution multiplexed computational imaging architecture utilizing micromirror arrays to steer sub imager fields of view

A thin, agile multiresolution, computational imaging sensor architecture, termed PANOPTES (processing arrays of Nyguist-limited observations to produce a thin electro-optic sensor), which utilizes arrays of micro electromechanical mirrors to adaptively redirect the fields of view of multiple low-resolution sub imagers, is described. An information theory-based algorithm adapts the system and restores the image. The modulation transfer function (MTF) effects of utilizing micromirror arrays to steering imaging systems are analyzed, and computational methods for combining data collected from systems with differing MTFs are presented.

[2] Fast and Robust Multiframe Super Resolution

Super-resolution reconstruction produces one or a set of high-resolution images from a set of low-resolution images. In the last two decades, a variety of super-resolution methods have been proposed. These methods are usually very sensitive to their assumed model of data and noise, which limits their utility. This paper reviews some of these methods and addresses their shortcomings. This paper propose an alternate approach using 1 norm minimization and robust regularization based on a bilateral prior to deal with different data and noise models. This computationally inexpensive method is robust to errors in motion and blur estimation and results in images with sharp edges. Simulation results confirm the effectiveness of our method and demonstrate its superiority to other super-resolution methods.

[3] Extraction of high-resolution frames from video sequences

The human visual system appears to be capable of temporally integrating information in a video sequence in such a way that the perceived spatial resolution of a sequence appears much higher than the spatial resolution of an individual frame. While the mechanisms in the human visual system that do this are unknown, the effect is not too surprising given that temporally adjacent frames in a video sequence contain slightly different, but unique, information. This paper addresses the use of both the spatial and temporal information present in a short image sequence to create a single high-resolution video frame. A novel observation model based on motion compensated sub sampling is proposed for a video sequence. Since the reconstruction problem is ill-posed, Bayesian restoration with a discontinuity-preserving prior image model is used to extract a high-resolution video still given a short low-resolution sequence. Estimates computed from a low-resolution image sequence containing a sub pixel camera pan show dramatic visual and quantitative improvements over bilinear, cubic B-spline, and Bayesian single frame interpolations. Visual and quantitative improvements are also shown for an image sequence containing objects moving with independent trajectories. Finally, the video frame extraction algorithm is used for the motion-compensated scan conversion of interlaced video data, with a visual comparison to the resolution enhancement obtained from progressively scanned frames.

[4] Image Deblurring and Super-Resolution by Adaptive Sparse Domain Selection and Adaptive Regularization

As a powerful statistical image modeling technique, sparse representation has been successfully used in various image restoration applications. The success of sparse representation owes to the development of the l1-norm optimization techniques and the fact that natural images are intrinsically sparse in some domains. The image restoration quality largely depends on whether the employed sparse domain can represent well the underlying image. Considering that the contents can vary significantly across different images or different patches in a single image, we propose to learn various sets of bases from a precollected dataset of example image patches, and then, for a given patch to be processed, one set of bases are adaptively selected to characterize the local sparse domain. We further introduce two adaptive regularization terms into the sparse representation framework. First, a set of autoregressive (ar) models are learned from the dataset of example image patches. The best fitted ar models to a given patch are adaptively selected to regularize the image local structures. Second, the image nonlocal self-similarity is introduced as another regularization term. In addition, the sparsity regularization parameter is adaptively estimated for better image restoration performance. Extensive experiments on image deblurring and super-resolution validate that by using adaptive sparse domain selection and adaptive regularization, the proposed method achieves much better results than many state-of-the-art algorithms in terms of both psnr and visual perception.

[5] Robust Multichannel Blind Deconvolution via Fast Alternating Minimization

Blind deconvolution, which comprises simultaneous blur and image estimations, is a strongly ill-posed problem. It is by now well known that if multiple images of the same scene are acquired, this multichannel (MC) blind deconvolution problem is better posed and allows blur estimation directly from the degraded images. Improved the MC idea by adding robustness to noise and stability in the case of large blurs or if the blur size is vastly overestimated. Formulate blind deconvolution as an l_1 -regularized optimization problem and seek a solution by alternately optimizing with respect to the image and with respect to blurs. Each optimization step is converted to a constrained problem by variable splitting and then is addressed with an augmented Lagrangian method, which permits simple and fast implementation in the Fourier domain. The rapid convergence of the proposed method is illustrated on synthetically blurred data. Applicability is also demonstrated on the deconvolution of real photos taken by a digital camera.

III. PROBLEM STATEMENT

For both BD and SR, techniques are proposed in the literature for reconstruction from a single image or multiple images. Multi-image super-resolution (MISR or shortly) methods reconstructs one HR image by fusing from multiple LR images.

By contrast, single-image super-resolution (SISR) methods, which are also known as learning-based, patch-based or example-based SR techniques, are proposed in which small spatial patches within the input LR image are replaced by similar higher resolution patches previously extracted from a number of HR images.

In comparison with MISR methods, SISR methods do not need motion and blur estimation processes, but have a lower performance instead. In case of BD, the most proposed methods are for reconstruction from a single image (SIBD).

However, multi-image BD (MIBD) methods are also developed to boost the reconstruction performance. LR images given to a SR (MISR) system mostly have sub-pixel displacements between their fields of view (FOV). Also both SR and MIBD systems may either use LR images that have differences in their point spread functions (PSFs) due to variations in the parameters of the lens (such as aperture, focal length, and focus), or use LR images with variances in their illumination conditions (photometric variations) due to dissimilar camera parameters (such as exposure time and aperture size).

Most publications on BD/SR are non-blind, i.e., they do not explicitly consider blur identification during the reconstruction procedure. Many studies assume that the PSFs are fully known a priori due to capturing images under controlled environmental/imaging conditions. Other works assume that the amount of blur is negligible and can be omitted from the reconstruction.

While these simplifications are valid under certain circumstances, they are impractical for many real-world applications in which varying blurring effects may accompany their imaging process. In parallel to these works, others have studied blur identification along with BD/SR. These papers can be classified into two main categories: methods that consider blur identification and image restoration as two disjointed processes and methods that combine these two processes into a unified procedure, e.g. alternating minimization (AM).

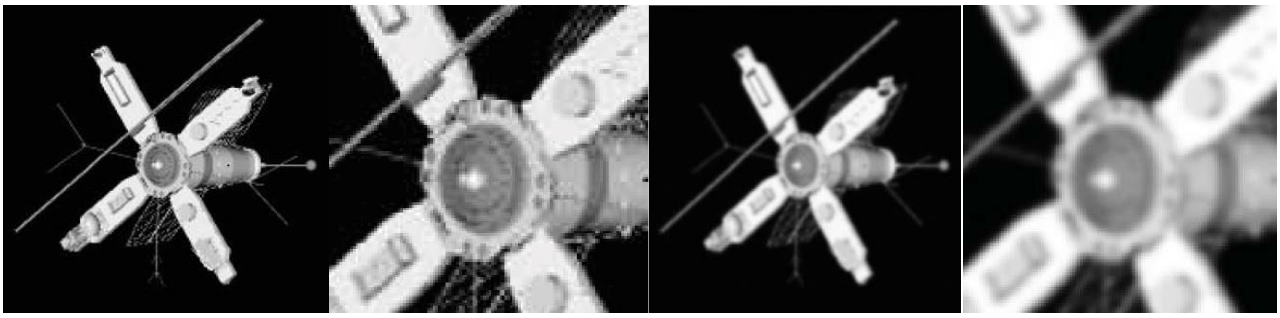
IV. PROPOSED METHOD

The proposed kernel (blur) estimation procedure is based on three important findings of fact:

1) Edges and their neighboring regions are more useful in blur estimation;
2) It is more accurate to start the blur estimation with just a few salient edges and progressively allow more and more edges to contribute; and
3) Blur estimation in the filter domain is more efficient than the pixel domain. The first fact is supported by preprocessing the reconstructed image using an edge emphasizing smoothing operation which aims to enhance soft edges toward step edges while smoothing out weak structures.

The second fact is achieved by setting large values for the regularization coefficients of both the HR image and the smoothing function in the initial iterations, and decreasing these values gradually at every iteration. The last fact suggests the use of the gradients of the LR and preprocessed HR images instead of their pixel values for the blur estimation. By the use of Gaussian (L2-norm) prior(s) for the blur(s), the blur estimation procedure will be solely based on convolution and multiplication-by-constant operations, and so the blur(s) can be updated fast by pixel-wise multiplications and divisions in the frequency domain.

While in the MIBD reconstruction the input LR images have different blur parameters, in reality all inputs (LR images) to motion-based SR systems (in contrast to motion-free SR systems) have equal blurs and noise levels since they are mostly continuous shots of an image camera, successive frames of a video sequence, or simultaneously captured by several cameras of equal type and settings. Even the works that do not explicitly consider this assumption in their models almost test their proposed algorithms on such images. This assumption enables us to separate the registration and up sampling processes from the optimization procedure. We found that in this way, on one hand, the quality of the estimated blur (and so the estimated HR image) is improved, and on the other hand, the optimization speed is increased several times.



(a) **(b)**

Fig.1: Blind SIBD for the Satellite image. (a) Ground-truth image. (b) Blurred image.

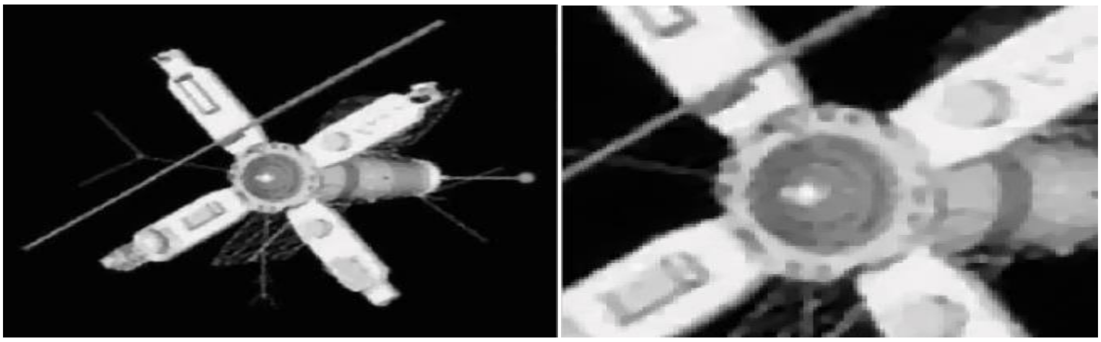
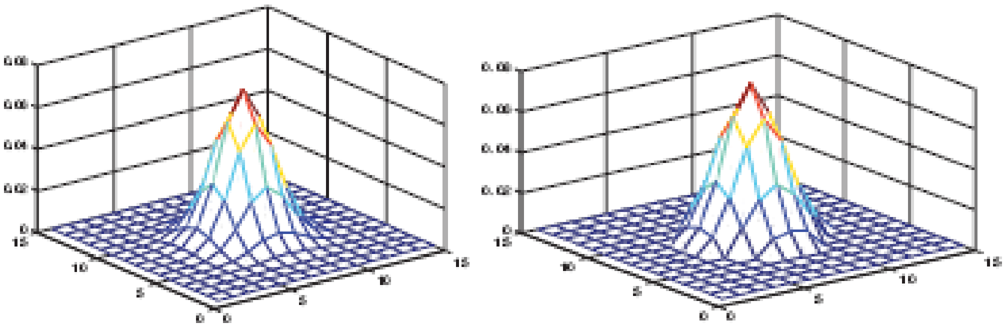


Fig. 2: Reconstructed image of proposed method with PSNR of 31.1 dB.



(a) **(b)**

Fig. 3: (a) Original Gaussian PSF. (b) Estimated PSF of proposed method with NMSE of 0.01

Advantages

The proposed blur estimation procedure preprocesses the estimated HR image by applying an edge emphasizing smoothing operation which enhances the soft edges toward step edges while smoothing out weak structures of the image. The parameters are altered so that more and more salient edges are contributed in the blur reconstruction at every iteration. For better performance, the blur estimation is performed in the filter domain using the derivatives of the preprocessed HR image and the LR image(s).

V. SYSTEM REQUIREMENTS

Hardware Requirements

- Intel Pentium IV Processor
- 2 GB RAM
- 20 GB HDD

Software Requirements

- Operating System: Windows XP SP-3, Windows 7
- Matlab (version R2012b)

VI. CONCLUSION

A novel blind method is presented for multi-image super-resolution (MISR), single/multi image blur deconvolution (S/MIBD). MIBD accepts multiple LR images with different blurs, without spatial displacements. In the proposed MISR method accepts number of LR images with subpixel displacement but the same blur function and noise parameters used. The proposed blur estimation method preprocesses the estimated HR image by applying edge emphasizing operation. In every iteration parameters are altered so that more salient edges contributed in blur reconstruction. For blur estimation filtering domain is used which improves the performance. The future enhancement would be on video deblurring.

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