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Blur Deconvolution and Super Resolution of Image using Unified Blind Method

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Abstract:
Image deblurring is the process of obtaining the original image by using the knowledge of the degrading factors. Degradation comes in many forms such as blur, noise, and camera misfocus. Blind image deconvolution is an image restoration technique that permits recovery of the target scene from a single or a set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF). It is very crucial part of image deblurring to recover image without the knowledge of the reason of its degradation. Here, an estimate is done about the unknown degradation function and using that, an estimate of the original image is produced. This paper presents 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 Gaussian noise (AWGN). 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. Experimental results confirm the robustness and effectiveness of the proposed method.

Key words: *Blur Deconvolution, Blur Estimation, Image Restoration, Super Resolution, Point Spread Function (PSF), High Resolution (HR), Low Resolution (LR), Alternating minimization (AM)*

1. Introduction

Image deblurring refers to the recovery of an original image from degraded observations [20]. The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. In cases like motion blur, it is possible to come up with a very good estimate of the actual blurring function and "undo" the blur to restore the original image. In cases where the image is corrupted by noise, the best may hope to do is to compensate for the degradation it caused. There are two broad categories of image restoration such as Image deconvolution and Blind Image Deconvolution. Image deconvolution is a linear image restoration problem where the parameters of the true image are estimated using the observed or degraded image and a known Point Spread Function.

Blind Image Deconvolution is a more difficult image restoration method where image recovery is performed with little or no prior knowledge of the degrading PSF. The advantages of deconvolution are higher resolution and better quality. The main aim of Blind Image Deconvolution (BID) is to recover the original image from a degraded image which is blurred by an unknown degradation function, commonly by a Point Spread Function. This Technique allows the reconstruction of original images from degraded images even when we have very little or no knowledge about the PSF.

This paper is structured as follows: Section II describes the related work. Section III represents unified blind image deconvolution approach, and its procedure. Section IV describes the overall architecture of proposed work. Section V describes experimental results for restored images using our proposed method. Section VI describes conclusion.

2. Related Work

F. Sroubek and P. Milanfar[13] proposed, multichannel (MC) blind deconvolution problem which is better posed and allows blur estimation directly from the degraded images. Multichannel blind deconvolution can be improved by adding robustness to noise and stability in case of large blurs or if the blur size is vastly overestimated. Solution to blind deconvolution is formulated as a regularized optimization problem and seeks 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.

F. Sroubek and J. Flusser[14] put forth an alternating minimization scheme based on maximum aposterior estimation with a priori distribution of blurs derived from the multichannel framework and a priori distribution of original images, defined by the total variation semi-norm. Stochastic approach enables users to recover the blurs and the original image from channels severely corrupted by noise.

W. Freeman, T. Jones, and E. Pasztor [9] has proposed a technique that divides a large volume of images into small rectangular pieces called “patches” and brings them together in a dictionary as patch pairs of low resolution and high resolution images. This method consists of two phases; dictionary construction phase and super resolution phase. Dictionary construction phase performs extraction of patch pairs from both high resolution and low resolution images and stores them as a data in the dictionary. Super resolution phase performs synthesizing of high resolution images by searching patches stored in the dictionary that are best matched to the input images.

F. Sroubek, G. Cristobal, and J. Flusser[18] has proposed, a new approach to the blind deconvolution and super resolution problem of multiple degraded low-resolution frames of the original scene. The approach consists of building a regularized energy function and minimizing it with respect to the original image and blurs, where regularization is carried out in both the images and blur domains. The image regularization based on variational principles maintains stable performance under severe noise corruption. The blur regularization guarantees consistency of the solution by exploiting differences among the acquired low-resolution images.

R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman [12] presented, camera shake during exposure leads to objectionable image blur and ruins many photographs. Approach introduces a method to remove the effects of camera shake from seriously blurred images. The method assumes a uniform camera blur over the image and negligible in-plane camera rotation. In order to estimate the blur from the camera shake, the user must specify an image region without saturation effects.

3. Proposed Method

3.1. Non-Uniform Interpolation

Non-uniform interpolation is a common procedure in image processing. Non-uniform interpolation, also known as scattered interpolation, is a key step in image super-resolution from multiple images [16].

Given a set of degraded LR frames $\{f_K\}_{k=1,\ldots p}$ each M X N pixels in dimension. Fig1 illustrates the non-uniform interpolation of LR frames. The figure shows three 4 X 4 pixel LR frames on an 8 X 8 HR grid. Each symbol (square, circle, triangle) indicates the sampling points of a frame with respect to the HR grid. We pick an arbitrary frame as a reference frame; in this case, the frame marked by the circular symbols. The sampling grid for the triangular frame is a simple translation of the reference frame grid. The difference between the sampling grid for the square frame and the reference frame grid includes translational, rotational, and magnification (zoom) components.

The goal of resolution enhancement is to interpolate and restore values at the HR grid points. After the input low resolution (LR) images are registered to the

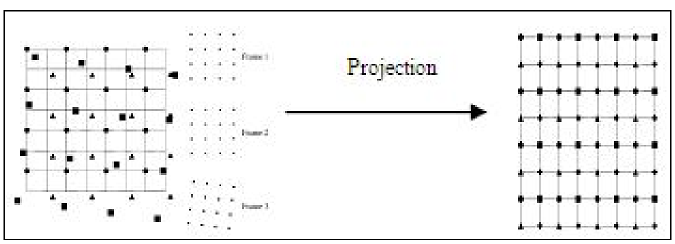

Figure 1: Non-uniform Interpolation of LR frames

high resolution (HR) grid, these can be combined (with appropriate offsets) to form a compound non-uniformly sampled image. An interpolation procedure such as linear, bilinear, or spine can be applied to resample the compound image at the uniform positions of the high-resolution grid.

3.2. Image Estimation

The up-sampled image obtained from non-uniform interpolation, is still blurry and noisy, but free of aliasing. We use the following cost function [5] for estimating the HR image ***f***:

$$J(f) = \sum_{k=1}^{N} \| z_k - H_k f \|^2 + \lambda \left\| \rho\left(\sqrt{\sum_{j=1}^{4} (B_k f)^2}\right) \right\|_1 \quad (1)$$

where N is equal to 1 for the SR and SIBD problems, but greater than 1 for the MIBD case, and z_k is the blurry image obtained from non-uniform interpolation pixels, B_k is the convolution matrix, H_k is the kth blurring operator.

The cost function at iteration n, and the optimum value of $\boldsymbol{f}^n$ is computed by solving the following linear equation:

$$\boldsymbol{f}^n = \boldsymbol{A}^{n-1} \boldsymbol{b}^n \quad (2)$$

We adopt the CG iterative method to solve this equation. It converges faster than the other existing methods and its variations which are widely used to solve the optimization problems. The complexity of CG is *O (n)*.CG is a vector-based method and it requires less storage and its implementation is also simpler. Thus, in terms of efficiency, speed, and simplicity, CG is a suitable choice.

3.3. Psf Estimation

In a blind image deconvolution problem, more accurate estimation for the blur (and subsequently for the image) can be obtained in the blur(psf) estimation process[22], the estimated image in image estimated step $\boldsymbol{f}$ is pre-processed by an edge-emphasizing smoothing operation. In proposed work, we use the edge-emphasizing smoothing method of [21] which is applied at each AM iteration [13] to $\boldsymbol{f}$. This method manageably and globally removes a significant amount of low-amplitude structures via L_0 gradient minimization. It penalizes the number of non-zero gradients by minimizing the following cost function [5]:

$$\boxed{J(s^n) = \| s^n - f^n \|^2 + \beta^n \# \{p \,|\, |(\nabla_x s^n)_p| + |(\nabla_y s^n)_p| \neq 0\}} \qquad (3)$$

where $\mathbf{s}^n$ is the output of the edge-emphasizing smoothing algorithm at the k^{th} AM iteration, $\nabla = [\nabla_x, \nabla_y]$ is the gradient operator, $\#\{\cdot\}$ is the counting operator, and $(\cdot)_p$ indicates the value of the underlying vector at the pixel location p. No pre-smoothing is required before using this smoothing operation.

The cost function [5] we use for the blur (psf) estimation is:

$$\boxed{J(h^n) = \sum_{k=1}^{N} \sum_{i=1}^{2} \| C_i z - C_i S^n h_k^n \|^2 + \gamma \sum_{k=1}^{N} \sum_{j=1}^{4} \| B_j h_k^n \|^2} \qquad (4)$$

where $\mathbf{C}_1$ and $\mathbf{C}_2$ are the convolution matrices of the gradient filters c_1 and c_2 in the horizontal and vertical directions, and S^n is the convolution matrix of $\boldsymbol{s}^n$. This can be directly computed in the Fourier domain using Parseval's theorem [5]:

$$\boxed{h_k^n(x, y)}$$

$$\boxed{= \mathcal{F}^{-1}\left(\left[\sum_{i=1}^{2} \overline{[\mathcal{F}(c_i) \times \mathcal{F}(s^n)]} \times [\mathcal{F}(c_i) \times \mathcal{F}(z)] \right] / \left[\sum_{i=1}^{2} |\mathcal{F}(c_i) \times \mathcal{F}(s^n)|^2 + \gamma \sum_{j=1}^{4} |\mathcal{F}(b_j)|^2 \right] \right)} \qquad (5)$$

where $k = 1, \ldots, N$, $F(\cdot)$, and $F^{-1}(\cdot)$ denote FFT and inverse-FFT operations, and $\overline{(\cdot)}$ is the complex conjugate operator. We use the MATLAB function edgetaper(·) to avoid boundary artefacts as a result of performing deconvolution in the Fourier domain. In the initial iterations of the algorithm that the estimated image is still blurry, we use large values for regularization coefficient values to apply more smoothness to the estimated image and allow fewer salient edges to contribute in the blur estimation.

3.4. Overall Estimation

We use a coarse-to-fine scheme to perform initial estimates of the image and blur kernels in lower scales using down-sampled versions of the observed LR images. After a few AM iterations at each scale, the estimation results are up-sampled using bilinear interpolation and used as the inputs of the next level. This scheme not only increases the processing speed, but also helps to avoid local minima.

4. Overall Architecture

The main focus of this proposed work is to deblur an original image from a degraded image that has been degraded by some unknown sources. The proposed method deals with when input image is loaded, generation of a low resolution image by convolution operation and by adding noise. Perform non uniform interpolation of LR images, in which, the pixel values of all LR images are registered and projected to the HR image grid, and then, the HR image pixel values are computed through an interpolation scheme such as linear, cubic, or spline. The obtained image is still blurry and noisy, but free of aliasing, then apply deblurring algorithm, to get a deblurred image. The overall architecture of the proposed approach is explained in figure bellow.

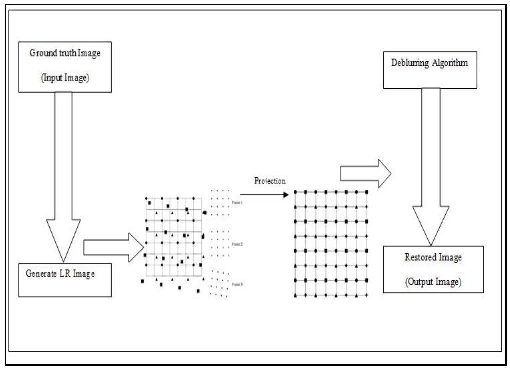

Figure 2: overall architecture of proposed method

The whole process of proposed method based on Blind image deconvolution i.e. described by the following flowchart.

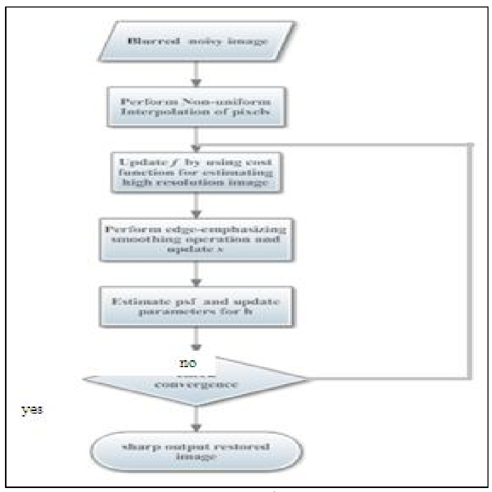

Figure 3: Flowchart of proposed method

5. Experimental Result

The proposed approach is experimented using a test image "cameraman.jpg" of size 256 x 256.The below images represent the result of blurred image, created by convolution and restored image.

Figure 4: Original image

- Image shown in Figure 4 represents the original image "cameraman.jpg" of size 256 x 256.


Figure 5: Blurred Image


Figure 6: Restored Image

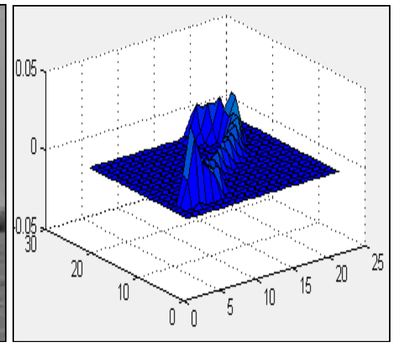
Figure 7: Estimated psf

6. Conclusion

A blind unified deconvolution method for image restoration is presented. The inputs to the deblurring algorithm are several LR images with different blurs. The assumption of blur and noise similarity in proposed method allows to separate the registration and up-sampling processes from the reconstruction procedure. The blur estimation procedure pre-processes 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 will be performed in the filter domain using the derivatives of the pre-processed HR image and the LR image(s). An experiment result confirms the performance of the proposed method.

7. References

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