High Resolution Image Estimation using Restoration Technique

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Abstract

The blur, aliasing, and additive white Gaussian noise are artifacts which corrupts the low-resolution images. The simultaneous estimation of volatile blurs and high resolution images by using unified blind method. The complexity in super-resolution is solved by minimizing a regularization of energy function. The regularization is carried by both image and blur domains. Variational integral method for image regularization with good edge-preserving capabilities and blur regularization is based on blur estimation. The Huber-Markov random field (HMRF) model, is used for image regularization which is a type of variational integral that produce the piecewise smooth nature of the HR image. The supported blur estimation process is carried by using bilateral filtering and sharp filtering. An edge-emphasizing smoothing operation, which improves the quality of blur estimation by enhancing strong soft edges toward step edges and weak structures can be filtered.

Index Terms—*Super-resolution, Blind deconvolution, Bilinear Interpolation, Huber-Markov Random Field, Bilateral filtering and Sharp filtering.*

I. INTRODUCTION

In conventional high-resolution (HR) imaging systems need high-cost and bulky optical elements whose physical sizes state the light-gathering ability and the resolving power of the imaging system. In difference, computational imaging systems combine the power of digital processing with data gathered from optical elements to create HR images. Aliasing, blurring, and noise are the artifacts may affect the spatial resolution of an imaging system, this fine details produces the low-resolution which can be obtained from the captured images.

Blur deconvolution (BD) and super-resolution (SR) are two groups of techniques to obtain the clear resolution of the images. The most difference between these two groups is that the goal in a BD difficulty is just to loosen blurring and noise, whereas Super-resolution technique also removes or reduces the effect of aliasing . The unified method is carried because input and output images are same for blind deconvolution and the output image for super-resolution is larger than the input image. The other difference is that since severe blurs remove 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. For both BD and SR, techniques are proposed for reconstruction from a single image or multiple images. By contrast, single-image super-resolution methods, which uses classical super-resolution and example-based SR techniques for small spatial patches within the input LR image are replaced by similar higher resolution patches formerly extracted from a different HR images.

For Blur Deconvolution, the most methods are proposed for reconstruction from a single image. However, image Blur Deconvolution methods are also developed to enhance the reconstruction routine. In the fields of view LR images given to a SR system mostly have sub-pixel displacements .Also both SR and BD 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.

The proposed unified approach for super-resolution and blind deconvolution to obtain original image. The cost function for the output HR image includes a prior based on Huber-Markov random field (HMRF) model. The HMRF prior is rounded but not quadratic; however using the lagged diffusivity fixed-point (FP) scheme, it can be replaced with a quadratic form at each iteration of the optimization process. This strategy allows for employing efficient iterative optimization methods like conjugate gradient (CG) to solve the optimization problem.

This paper is organized as follows: Section II explains the image formulation. The proposed method is represented in Section III. And finally Section IV discusses conclusions and future research directions.

II. IMAGE FORMULATION

In matrix notation the low-resolution image can be formed with convolution of warping image and blurring operator with addition of noise can be given as,

$$g_k = D_k H_k S_k f + n_k$$

The original HR image is warped, convolved with on the whole system PSF, down-sampled and finally corrupted by noise to generate each LR image. Noise such as additive white Gaussian noise and salt and pepper noises can be added. where f is the high-resolution input image, S_k and H_k are the kth warping (motion) and blurring operators. D_k is the down-sampling matrix , g_k and n_k are the vectors of the kth LR image and noise respectively. In the BD problem, D_k and S_k are identity matrices I. That for the SR problem, the blurs in all LR images are the same.

Although the amount of publications on blind BD is quite extensive, the literature on blind multi-image SR is very limited due to the difficulty of coping with the down-sampling operation in blur estimation. A unified method for blind BD and SR in which the well-known TV regularization is used as the image prior. While this prior is able to properly estimate the HR image even when the LR images have different blurs, the estimated PSFs are with some inevitable ambiguity. By contrast, in the proposed method produces better solution in estimating the blurs since our method is intrinsically designed to make noise and blur are equal.

Another work on blind SR using the MAP framework is suggested in which the cost function for estimating the HR image includes a Total Variant prior using bilateral filtering. The blur identification process consists of three optimization steps: first, initial estimates of the blurs using the Gaussian Markov Random Field priors. The most important limitation of this work is that considering just a few parametric models does not cope with the diversity of blur functions in reality. Also the estimated blurs are not verified and the reported PSNR values for the estimated HR images are low.

III. PROPOSED METHOD

A. Non-uniform Interpolation

Since for the SR problem we assume that all LR images have identical PSFs and noise levels. When the PSF is LSI and isotopic, and the perceived motions are rigid but non-global (local), is the commutability of warping and blurring operations holds for all pixels except for those on and near (within the PSF supports) the boundaries of moving objects. In these situations, the imaging model can be rewritten as,

$$g_k = D_k H_k S_k f + n_k = D_k S_k z + n_k$$

where **z** is the up-sampled (anti-aliased) but still blurry image. When noise is the same for all images, an appropriate way to reconstruct **z** is using multi-frame non-uniform interpolation which directly reverses the reconstruction process. The concept of this method is shown is shown in Fig. 1 in which, first, the pixel values of all LR images are registered and projected to the HR image lattice, and then, the HR image pixel values are computed through an interpolation methods such as bilinear, , spline or cubic.

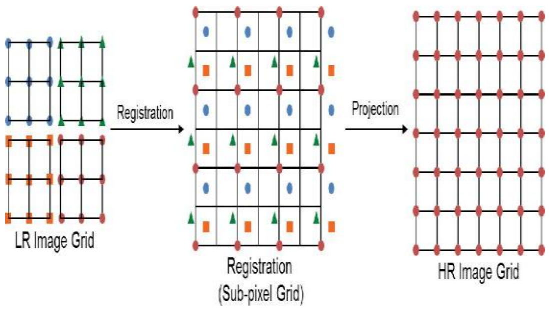


Fig.1.Non-Uniform Interpolation of LR Images.

In most non-blind SR reconstruction methods, registration and up-sampling operations are performed within the image estimation process. However, our experiments show that for a blind SR problem with identical blurs and noise level, by separating the up-sampling and registration operations from the reconstruction process, both speed and precision of the blind estimation are increased.

Bilinear interpolation can be used where perfect image transformation with pixel matching is impossible, so that can calculate and assign appropriate intensity values to pixels. Comparing other interpolation techniques such as nearest neighbor interpolation and bicubic interpolation, only the 4 nearest pixel values are used by bilinear interpolation which is located in diagonal directions from a given pixel in order to find the appropriate color intensity values of that pixel. Bilinear interpolation considers the closest 2x2 neighborhood of known pixel values surrounding the unknown pixel's computed location. A weighted average of these 4 pixels of an image can be taken to arrive at its concluding, interpolated value. The weight on each of the 4 pixel values is based on the computed pixel's distance from each of the known points. The advantage of bilinear interpolation is fast and simple to implement.

B. Image Optimization

To optimize a cost function with the HMRF prior, in the gradient projection method, and in the damped Newton method are employed. The iterative method to optimize the cost function is Conjugate Gradient (CG). However, since the cost function is non-quadratic, its gradient is nonlinear. Thus it is not possible to directly use CG as it can only operate on linear systems.

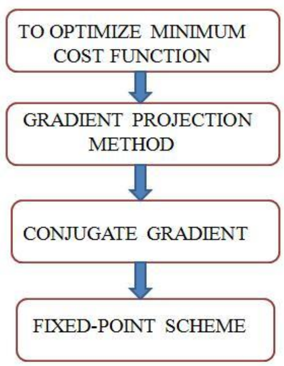


Fig.2 Image optimization

The fixed-point (FP) scheme is to linearize the gradient of the HMRF prior through lagging the diffusive term by one iteration. The CG iterative method for it converges faster than the steepest descent method and its variations which are widely used to solve the optimization problems. Consequently, these Newton-type methods are computationally more expensive than CG. While the complexities of the Newton and quasi- Newton methods are of orders $O(n3)$ and $O(n2)$, respectively, the complexity of CG is $O(n)$. Thus, in terms of efficiency, speed, and simplicity, CG is a suitable choice.

The lower complexity is important in large size optimization problems like image analysis. Moreover, many efficient methods such as Newton, Gauss-Seidel, Bi CG, etc. are based on matrix calculation. In contrast, CG is a vector-based method and can be totally implemented as the concatenations of filtering and weighting operations, so it requires less storage and its implementation is also simpler.

The cost function for the output HR image includes a prior based on Huber-Markov random field (HMRF) model. This variational type prior suppresses noise while preserving edges.

C. Blur Optimization

The more accurate estimation for the blur can be obtained in a blind image deconvolution problem, if in the blur estimation process, the ***f*** is estimated image can be preprocessed by an edge-emphasizing smoothing operation. This has a optimistic effect on the excellence of the blur estimate from the following aspects: 1) From salient edges blur can be estimated best and their adjacent pixels, so by smoothing ***f*** weak edges and also false edges caused by ringing are smoothed out and do not contribute to the blur estimation; 2) In non-edge regions noise has a stronger adverse effect than in edge regions, so smoothing the non-edge regions helps in civilizing the blur estimation; and 3) The ground-truth images are assumed to have sharp and binary-like edges, therefore, replacing soft edges with step edges in ***f*** provides a closer estimate of the ground-truth image and assists in getting better blur estimation, especially in the initial steps of the blind optimization where the estimated image ***f*** is still rather indistinct.

To smooth out non-edge regions and improve the sharpness of edges the shock filtering operation is used by which a ramp edge gradually approaches a step edge through a few iterations. Since the performance of the shock filtering and some other edge-emphasizing smoothing techniques are influenced by noise, the image is pre-smoothed. The bilateral filtering method is used before applying the shock filter.

A non-linear, edge-preserving and noise-reducing smoothing filter for images is a bilateral filter. By using bilateral filtering the intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. The weight of pixel can be based on a Gaussian distribution. The weights of pixel not only depend on Euclidean distance of pixels, but also on the radiometric differences. The sharp edges can be preserved by analytically looping through each pixel and adjusting weights to the nearby pixels accordingly.

To create a shock between two influence zones in a much localized manner in order, one belonging to a maximum and the other to a minimum of the signal. By iterating this process according to a small time increment, that can ultimately obtain a piecewise constant segmentation of the input image, thus leading to a deblurred output.

The deconvolution is the most familiar method used for deblurring. Deconvolution is an algorithm-based process used to reverse the effects of convolution of recorded data. There are two major ways for deblurring images. Non-blind algorithms use deconvolution with the help of external information like another extra image and blind algorithms use a single image for deblurring.

By combining two degraded images a deblurring technique produces one high quality image. They are blurred image and a noisy image. Both images are used to estimate an accurate blur kernel, which otherwise is difficult to estimate from a single blurred image. In further stage, using both images a remaining deconvolution is proposed to significantly reduce ringing artifacts inherent to image deconvolution.

D. Overall Optimization

To achieve initial estimates of the image and blur kernels in lower scales using down-sampled versions of the experimental LR images. After a few alternate minimization 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. The PSNR and MSE values can be measured.

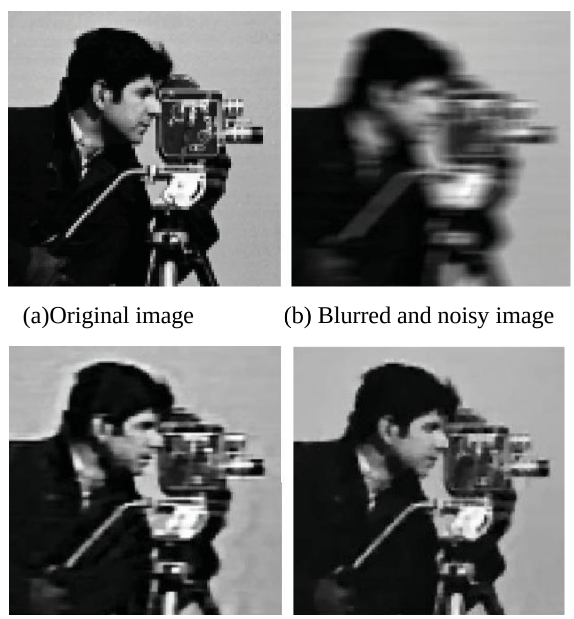
The Signal-to-noise ratio is a measure that compares the level of a preferred signal to the level of surroundings noise. It can also be defined as the ratio of signal power to the noise power, often expressed in decibels. The Peak signal-to-noise ratio is termed as the ratio between the maximum possible power of a signal and the power of degrading noise that affects the reliability of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of restoration of lossy compression . The signal is the original data, and the noise is the error introduced by compression. When comparing compression, PSNR is an approximation to human perception of reconstruction quality. Although a larger PSNR generally indicates that the reconstruction is of larger quality.

The Mean squared error (MSE) of an estimator measures the average of the squares of the errors, that is the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. By measuring the Peak signal to noise ratio and normalized Mean square error value to optimize the accurate resolution of an image.

IV. RESULTS

The important contributions are an useful model for image noise that accounts for its spatial distribution, and a local prior to hold back ringing artifacts. These two models interact with each other to improve unblurred image estimation even with a very simple and inaccurate initial kernel after the advanced optimization process is applied. The algorithm contains novel approaches to both blur kernel estimation and image restoration. To show the effectiveness of the algorithm in both of these steps as well as a whole, with a non-blind deconvolution.

Using super-resolution and blind deconvolution problem, more accurate estimation for the blur can be obtained. The complexity in images can be reduced. The obtained result is provided with good edge preserving capabilities. The blind algorithm recovers the size and shape of each kernel accurately. The resulting deconvolved images are significantly sharper and show relatively minimal ringing artifacts, which indicates that the kernels are accurate. The estimated motion blur kernels have almost the same shapes as the original. The deblurring results show that the fine details of the original latent images have been accurately recovered.



(a)Original image (b) Blurred and noisy image

(c) Reconstructed image (d) Deblurred image

Fig.3 Recovery of an original image

V. CONCLUSION AND FUTURE WORKS

The unified method for super-resolution and blur deconvolution can be used to reduce complexity in image. The image optimization is based on alternating minimization of a well defined cost function which consists of a HMRF prior for the HR image and blur optimization for each of the blur functions. The method accepts a number of image and blur estimation is done with other filtering operations.

The 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 images. This work can be extended in several directions, for instance to have space-variant blur identification, study joint image registration and restoration procedures, or consider compression errors in the forward model.

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