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RESEARCH ARTICLE

# Real-Time Iterated Shrinkage Deconvolution for Artifacts Images

**M. Sravanthi[1], V. Swathanthra[2]**
[1]PG Student, VGSE, Karimnagar, India
[2]Associate Professor, VGSE, Karimnagar,, India

[1] *Sravanthi.manchala4a4@gmail.com;* [2] *Swathi26v@gmail.com*

***Abstract— we propose a solution to the problem of boundary artifacts appearing in several recently published fast deblurring algorithms based on iterated shrinkage thresholding in a sparse domain and Fourier domain deconvolution. Our approach adapts an idea proposed by Reeves for deconvolution by the Wiener filter. The time of computation is less than doubles.***

***Keywords: - Deblurring; deconvolution; image processing; image restoration; iterated shrinkage thresholding; primal-dual methods; sparsity; Wiener filter***

## I. Introduction

In this paper, we address the classical problem of deconvolution, i.e., to find the original image when we know an observed image blurred by a known blur kernel and degraded by an additive Gaussian noise. We use a matrix notation so that the convolution of image with kernel is written as, where is a block Toeplitz matrix with Toeplitz blocks and is taken as a column vector got by stacking all columns of the image to one long vector. In this notation, our observation model can be written as , where  is a Gaussian noise of variance .

Matrix has more columns than rows because observation includes only pixels not influenced by the unknown area outside of image. Deconvolution is usually viewed from the probabilistic viewpoint as a maximum *a posteriori* probability problem, i.e., we look for image with the highest posterior probability, given an estimate of image prior probability distribution. For Gaussian noise, this is equivalent to minimization the prior probability distribution is never known exactly and must be estimated. In addition, its form must be chosen so that the functional could be minimized efficiently the main problem of the implementation in the Fourier domain is the introduction of boundary artifacts caused by the fact that is not circulant. In Reeves described a trick that transforms problem with such non-circulant _ to the circular de-convolution.

In recent years, a group of techniques has appeared based on the fact that natural images can be decomposed as a linear combination of few atoms from an over complete dictionary. The application of sparsity priors to deconvolution provides state-of-the-art results. A significant part of the corresponding research, including recent papers aims at improving the speed of these algorithms. The standard solutions of with the norm are based on convex programming and, as such, are relatively time-consuming. The development of iterated shrinkage thresholding techniques provided a convenient tool for simple and fast computation. For a good overview of early synthesis-based techniques describes the constrained split Bregman method including convergence proofs for the analysis-based formulation. Faster two-step methods were proposed in in the latter case including convex constraints and the proved quadratic convergence rate. A method suitable for parallel implementation and hybrid regularizers is given. For the latest developments in the area of more general primal-dual algorithms. Note that for the functional is not convex; for convergence properties.

The method presented in this paper relates to a special class of the iterated shrinkage thresholding methods accelerating computation using deconvolution in the Fourier domain. We propose a modification that removes boundary artifacts produced by division in the Fourier domain while keeping the speed close to that of the original methods.

## II. CONTRIBUTIONS

In the recent the algorithm minimizing alternates between shrinkage thresholding in a sparse domain and deconvolution in the Fourier domain, which converges to a satisfactory solution in a few iterations. The main problem of these algorithms is boundary artifacts, analogous to those we know from Wiener filtering.

In this paper, we show how to remove these artifacts without excessive slow down. Results improve significantly in terms of both the visual quality and the mean square error.

Our solution is inspired by an idea published in for the deconvolution with Tikhonov regularization, which transforms the problem with non-circulant to the circular deconvolution, with the blurred input image framed to a previously estimated border of a width corresponding to half of the PSF. The estimation of the border is stated as an inverse problem of significantly smaller dimension.

We extended this idea to the functionals minimized in each iteration of the analysis-based methods. The resulting procedure includes relatively time-consuming estimation of borders that the input images are framed to. If we apply this estimation in each iteration, the artifacts are almost perfectly removed, but the computation is noticeably slower than the original algorithm. In this paper, this algorithm. To speed-up the algorithm, the estimated borders can be reused during the subsequent iterations of the algorithm. In certain cases, it is sufficient to simply treat the boundaries using the MATLAB function edgetaper (part of the Image Processing Toolbox), which blurs the image borders so that the image can be considered approximately periodic. This is a simpler and faster alternative. However, as demonstrated in the experimental section, the more elaborate solutions (Algorithms II & III) can yield considerably better results, particularly for motion blur and, in general, for images with large differences in the intensity of the opposing sides of the image. The same approach can be used for the augmented Lagrangian method and the primal-dual method.

## III. ALGORITHM

In this section, we detail the proposed algorithm versions denoted of them are modifications of the iterative procedure. At the input, the algorithm needs the blurred images and corresponding PSFs. The user can adjust the number of iterations and parameters.

The algorithm is basically the original extended to the possibility of multiple images and with a simple treatment of boundary artifacts. Boundary pixels of the input images are first replicated to achieve the same size as the estimated image. Then, we apply the MATLAB edgetaper function to smooth the transition between the opposite sides of the images. In some cases, this procedure suppresses the artifacts so that the results are acceptable. This is typical for Gaussian-like blurs.

The second version treats boundaries rigorously in each main-loop iteration according to formulas derived, which results in the almost complete removal of boundary artifacts.

Its main disadvantage is a relatively slow speed. The problem is that, although it is usually sufficient to use only two iterations of conjugate gradients to estimate the boundaries in the original algorithms.

Recall that the main motivation is not only to remove the boundary artifacts but also to keep the speed close to that of the original algorithms.

Fortunately, the estimation of the border areas need not be very precise to reduce the artifacts. Our experiments showed that it is sufficient to run the estimation of boundaries only in the first one to three iterations and then reuse them in the subsequent iterations. This means that except for a small constant number of iterations, our procedure reduces to the computation of almost the same equation as in the original algorithm. Note that the augmented Lagrangian algorithm has almost the same form, except the addition and subtraction of an auxiliary variable.

Next, we analyze the number of critical time-consuming operations, which is the Fourier transform and transforms to and from a sparse domain which is basically of the same complexity as the original algorithm, with the other two versions. The number of iterations is denoted one to compute and the other to return from the Fourier domain after finishing the deconvolution step. In addition, we precompute and for each input image in each main-loop iteration. In addition to the operations in requires estimating borders. In our experiments, we use, which is sufficient because the borders are being refined during all the consecutive main-loop iterations.

The Complexity of such transform is usually either, where is the number of pixels. It is important to realize that even the computation of an asymptotically linear transform can take more than an FFT in practice, particularly for highly redundant dictionaries.

 

On the other hand, if we use the gradient as the analysis operator, its computation time is very fast. For example, for ten iterations, and for most common frames, the only about 50% more time than the original algorithms and less than twice the original time for the regularization . In languages with high overhead of other operations, such as MATLAB, the difference may be even smaller.

## IV. EXPERIMENTS

For this paper, we chose only the analysis-based splitting approach taken with norm and combined with two types of analysis operators: anisotropic TV and the union of translation-invariant Haar wavelets with dual-tree complex wavelets. The latter was shown to achieve a state-of-the-art quality of deconvolution in simulated experiments with circular convolution. However, we tested also the norm and other combinations of sparse transforms with slightly worse results in terms of ISNR but the same conclusions.

Figs. 2 and 3 demonstrate the effect of the better treatment of image boundaries. To evaluate deconvolution error, we work with simulated data. Standard images were blurred using artificial kernels and degraded by additive Gaussian noise. To demonstrate the speed of convergence, we used only five iterations and regularization. Note that in all our color experiments, all three color channels were deconvolved separately.

Fig1.original image

Fig2. Deblurred with undersize PSF

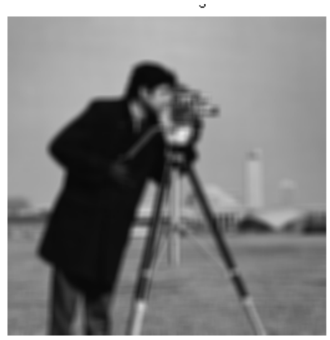

Fig3. Blurred image

 

Fig4. Restored image

## V. CONCLUSION

This paper presents a technique to remove boundary artifacts in recent nonblind deconvolution algorithms based on iterative shrinkage thresholding in a sparse domain and deconvolution in the Fourier domain.

We obtain an excellent quality of restoration, comparable with the current state of the art, while keeping the speed close to the high speed of the original algorithms. Our estimates of achievable frame rates indicate almost real-time performance even for 1-megapixel images on a personal computer.

Although the simple treatment of image boundaries can sometimes provide satisfactory results, the proposed solution gives a better alternative particularly for images with large differences in the intensity of the opposing sides of the image or motion PSFs. The proposed algorithm in its full version removes boundary artifacts almost perfectly, at the expense of higher time complexity. In addition, in most cases, the much faster approximative algorithm removes the artifacts sufficiently even if the boundaries are estimated only in the first main-loop iteration.

The rigorous treatment of boundaries is particularly important when working with small image patches because the importance of boundaries in such cases increases. One example is deblurring in the presence of space-variant blur solved by dividing the image into smaller blocks.

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