IMAGE RESTORATION
A New Explicit Approach in Filtering and Restoration of Digital Images

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Abstract: Image restoration, in presence of noise, is well known to be an ill-posed inverse problem. Deconvolution of blurry and noisy digital images is a very active research area in image processing. This paper introduces a novel approach composed of two optimized sequential stages of image processing: denoising followed by deconvolution. In the first stage, the denoising filter and the number of iteration are chosen in order to obtain the best value of the usual criteria and the good recovering of the blurry image. We assume that the statistics of the noise are previously estimated. In the second stage, a deconvolution method is applied on an almost noise free version of the blurry image. Compared with the classical deconvolution methods, the numerical experiments of proposed method, appear to give significant improvement. The preliminary results of the new cascade approach are very encouraging as well.

1 INTRODUCTION

It is well-known that the deconvolution of degraded images is a difficult and challenging problem. Because it is hard to recover the convolved original image, uniquely from the observed data. A fundamental issue in image restoration is blur removal from noisy observation.

The mathematical discrete direct model of observation is represented by the following equation

$$\mathbf{g} = \mathbf{h} * \mathbf{f} + \mathbf{n} \tag{1}$$

where the PSF is presented by $\mathbf{h}$ and $\mathbf{h} * \mathbf{f}$ means the output of the convolutive linear system. The term $\mathbf{n}$ in the equation (1) is non-correlated and independent additive observation noise. It is known that estimating the (*unknown*) true image $\mathbf{f}$ from observed image $\mathbf{g}$ is an ill-posed problem even if the PSF is known. The knowledge of the degradation model is, in general, insufficient to obtain satisfactory results. The blurry images are often disturbed and the process of restoration is eminently unstable in the presence of noise.

Many methods have been reported for restoring the degraded image under the assumption that the blur operator is exactly known (Biemond et al., 1990). The basic involved operation is simply a deconvolution process that faces the usual difficulties related to the noise and the ill-conditioning of the blur operator.

Many of the proposed methods are, therefore, structured in the context of regularization procedures to make the problem of inversion well-posed. The solution is, in general, regularized by introducing constraints translating prior knowledge on the original image and/or the PSF and/or the noise. Several approaches of regularization based on minimization of least squares error are possible in order to integrate *a priori* knowledge into the model of inversion. In this case, the *a priori* knowledge is expressed through the terms which are added to the basical *a posteriori* term of the least squares error. These terms represent a penalization, or a constraint on the restored solution. The mathematical formulation in the regularized image recovery problem, is stated as follows :

$$\widehat{\mathbf{f}} = \arg\min_{\mathbf{f}} \left[\|\mathbf{g} - (\mathbf{h} * \mathbf{f})\|^2 + \sum_i \lambda_i \Phi_i(\mathbf{f}) \right] \tag{2}$$

where the hyperparameters λ_i determine the weights of the terms of regularization Φ_i in the process of inversion.

This regularized inversion presents some disadvantages. In most of the methods of regularization, the knowledge of the noise is not directly translated in the term of regularization Φ_i. Taking into account of noise is often weighed by the hyperparameters λ_i. It is not easy to find a value of λ_i high enough to limit the influence of noise, and at the same time, weak enough

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to keep the maximum of details on original image. In some methods, like the stochastic approaches, it is possible to estimate the hyperparameters explicitly (Mohammad-Djafari, 1996), (Jalobeanu et al., 2002), but that requires an important computing time.

In the case of non-linear regularization, like the variational regularization methods, the process of inversion is, in fact, a spatial-variant deconvolution. In other words, the response of the reconstructed inverse filter depends on the local properties (edges, uniform areas, *etc.*) of the restored image. This is contradictory to the two-dimensional direct model of observation which occurs in linear optical system characterized by a spatial-invariant impulse response.

Recent research works (Bronstein et al., 2005), (Nikolova et al., 1998), (Park and Kang, 2006), (Molina et al., 2003), (Chantas et al., 2006), (Molina et al., 2006), (Likas and Galatsanos, 2004), have been developed to modify the terms of regularization in order to attenuate the noise over the uniform areas and to avoid the smoothing of the edges.

In the section 2 of this paper, we briefly mention the main idea of our approach. The numerical quantitative and visual experimental results of each stage are presented in subsections 2.1 and 2.2. Finally, we conclude the paper in section 3 by giving thoughts on future research.

2 PROPOSED APPROACH AND EXPERIMENTAL RESULTS

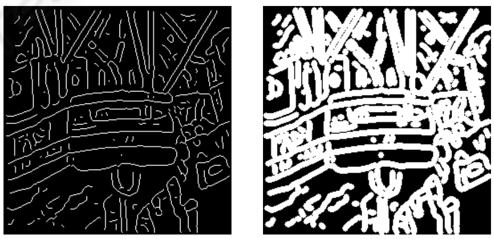
We split the restoration of blurry and noisy images into two sequential stages: denoising and deconvolution. It consists of applying first an algorithm of filtering adapted to the nature of the noise and then performing a deconvolution process on the filtered image.

The critical stage of the proposed approach is noise elimination. Because it has to accomplish the preservation of edges and fine details. But, it is also important to estimate the blurry image $\mathbf{h}*\mathbf{f}$ without altering it, nor the PSF. For these reasons, the choice of the filtering method is of the primary importance for our approach. To select the best filter, we have performed a comparative study of a set of representative filters requiring only the *a priori* knowledge on the noise. After this first filtering stage, two deconvolution processes (non-regularized and regularized) are evaluated.

2.1 Denoising Process

Six iterative filters were retained: Koenderink's filter (Koenderink, 1984), filter of Rudin *et al.* (Rudin et al., 1992), filter of Chan *et al.* (Chan et al., 2001), filter of Perona-Malik (Perona and Malik, 1990), Lee's filter (Lee, 1980) and filter of Beaurepaire *et al.* (Klaine, 2004). For all these filters, we follow an iterative denoising strategy for the purpose of evaluating the PSNR of the filtered images in each iteration. Invariably, these filters require the determination of a significant parameter in the process. This parameter is the *optimal iteration* where the PSNR of the filtered image is maximum.

The experiments were carried out on various series of images, synthetically degraded (defocusing blur with different diameters: 5, 7 and 9 and additive gaussian noise with different levels of standard deviation: 10, 14 and 16). Results are assessed first globally and then, locally. The global evaluation is obtained by calculing the three usual criteria MAE, MSE and PSNR for each filtering iteration number. These criteria are also considered to determine the influence of the estimator of $\mathbf{h}*\mathbf{f}$ on the final estimations of PSF and $\mathbf{f}$. For the local evaluation, the same criteria are selected but in three different zones: a zone containing the pixels of contours, a zone around these contours and the areas out of these two zones (cf. Figure 1).



(a) (b)

Figure 1: Local evaluation zones on degraded [LACORNOU]. image (defocusing blur $d = 7$, $\sigma_n = 14$). (a) Detected edges; (b) the zones around the edges(white) and the areas of out (black).

The PDE-based filters, Koenderick, Rudin *et al.*, Chan *et al.*, and Perona-Malik, give better results and among them, the filter of Chan *et al.* is slightly better with a low iteration number (cf. Table 1).

The results show that after a reasonable number of filtering iterations, the change in the PSF remains weak independently of the used denoising method and the selected initialization. These results remain valid whatever the size of PSF and the level of noise. The filter of Chan *et al.* gives appreciably better results. This filter will be retained for the denoising stage.

Table 1: Global and local evaluations of filters on degraded [LACORNOU] image (defocusing blur $d = 7$, $\sigma_n = 14$): PSNR values of $\widehat{\mathbf{h}*\mathbf{f}}$ corresponding to the optimal iteration number of filtering, calculated on the whole of image, on the contours, on the zones around contours and on the area out of them.

	$\widehat{\mathbf{h}*\mathbf{f}}$		contours		zone of contours		zone out of contours	
filter	iteration	PSNR	iteration	PSNR	iteration	PSNR	iteration	PSNR
Koenderink	27	34.812	16	13.149	24	36.712	37	39.765
Rudin *et al.*	103	34.255	109	**13.368**	106	35.643	100	39.90
Chan *et al.*	4	**35.124**	3	13.109	3	**36.875**	5	**40.341**
Perona-Malik	20	33.635	23	13.223	18	34.887	24	39.789
Lee	17	31.439	4	12.877	15	32.611	26	38.559
Beaurepaire *et al.*	2	30.655	0	12.789	1	32.549	2	35.583

2.2 Deconvolution Process

In this stage, we assume that the PSF is known. Two different deconvolution processes are examined. For both of them, an algorithm of conjugate gradient (CG) is considered to minimize the least squares criteria according to equation (2). For the first one, we minimize the least squares criteria without any prior knowledge on the original image. In this case, no regularization is considered in order to study the influence of filtering on the process of inversion and the quality of the restored image. For the second method, we regularize the process of deconvolution by penalizing highly oscillatory solutions. The motivation for using the regularization is due to the fact that the estimator of $\mathbf{h}*\mathbf{f}$ introduces a residual error. Thus, the influence of the residuals of the error on the filtered image can be reduced by slightly regularizing the process of inversion.

From numerous simulations, the experimental results show that when the level of noise is low, the non-regularized deconvolution gives slightly better results (cf. Table 2). The regularized method gives better results for higher level of noise. In both cases, the results of the proposed scheme, $\widehat{\mathbf{f}}(\widehat{\mathbf{h}*\mathbf{f}})$, are better according to the retained objective criteria, and compared to the results of the restoration obtained directly from observed image, $\widehat{\mathbf{f}}(\mathbf{g})$ (cf. Table 2, iteration number $= 0$, *i.e.* without filtering).

These results are also confirmed by the visual quality of the estimated images (Figure 2). Edges and details of the restored image are preserved.

It is clear that the optimal iteration number for stopping of the filtering depends strongly on the level of the noise and also the size of the PSF. As observed in Table 2, in the presence of noise ($\sigma_n \neq 0$), the results of restoration by using the filter of Chan *et al.* are systematically better than those without filtering (iteration number$=$ 0) for the different levels of the noise. The quantitative results show that the filter of Chan *et al.* associated with the regularized restoration method gives better PSNR with high level of noise. In the case of low level of noise, the non-regularized method gives slightly better PSNR values. The numerical experiments with other filters confirm the same results.

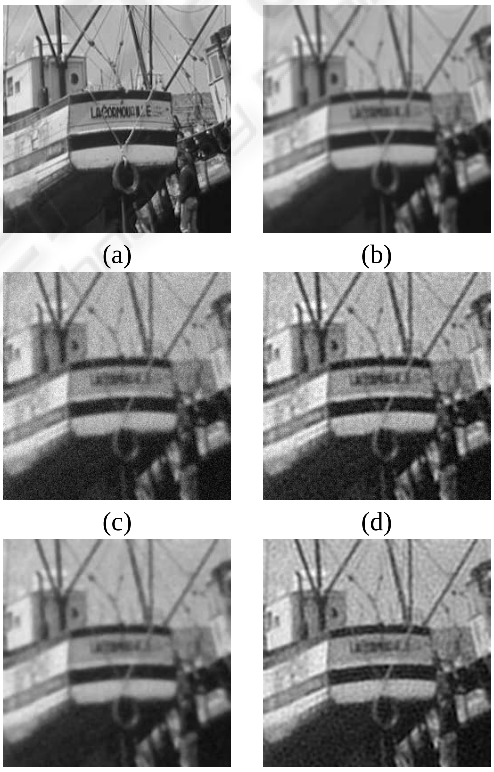


Figure 2: (a) original [LACORNOU] image; (b) blurry image $\mathbf{y}$ (defocusing blur $d = 7$); (c) blurry and noisy image (defocusing blur $d = 7$, $\sigma_n = 14$); (d) $\widehat{\mathbf{f}}(\mathbf{g})$ estimated from observed image; (e) filtered image $\widehat{\mathbf{h}*\mathbf{f}}$ obtained after 4 iterations by the filter of Chan *et al.*; (f) $\widehat{\mathbf{f}}(\widehat{\mathbf{h}*\mathbf{f}})$ obtained from image (e).

Table 2: Usual criteria values for non-regularized and regularized $\widehat{\mathbf{f}}$ obtained from $\widehat{\mathbf{h}.*\mathbf{f}}$ from degraded [LACORNOU] image (defocusing blur $d = 9$, and additive gaussian noise with various standard deviation levels σ_n =0, 8, 12 and 16) filtered by filter of Chan *et al*.

	$\widehat{\mathbf{h}*\mathbf{f}}$		non-regularized $\widehat{\mathbf{f}}$	regularized $\widehat{\mathbf{f}}$
σ_n	iteration	PSNR	PSNR	PSNR
0	0	Inf	**30.861**	**23.907**
8	0	30.046	10.952	23.101
	3	39.526	**23.663**	**23.534**
12	0	26.566	8.790	22.219
	4	37.127	**22.709**	**23.302**
16	0	24.134	7.837	21.255
	5	35.495	**22.005**	**23.062**

3 CONCLUSION AND FUTURE WORK

Both the numerical performance and visual evaluation of the results obtained by the proposed restoration method are significantly more favorable than that of the classical method without preliminary noise reduction. The numerical results indicate that the proposed scheme is quite robust and the image $\mathbf{f}$ can be recovered under presence of the noise even if it is high level. The quality of the restored image depends vigorously on the estimation of $\mathbf{h}*\mathbf{f}$, which means, the choice of the filter and the number of iteration are two important factors to get the satisfying results. We have evaluated a finite set of representative filtering methods in order to select the optimal one. The filter of Chan *et al*. achieves the best compromise between the quality of the filtering result and the number of iterations involved.

Primary results based on the estimation of the standard deviation of the filtering residuals are encouraging to solve the problem of the determination of the optimal iteration number of filtering.

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