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DECONVOLUTION BASED ON THE CURVELET TRANSFORM

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ABSTRACT

This paper describes a new deconvolution algorithm, based on both the wavelet transform and the curvelet transform. It extends previous results which were obtained for the denoising problem. Using these two different transformations in the same algorithm allows us to optimally detect in the same time isotropic features, well represented by the wavelet transform, and edges better represented by the curvelet transform. Adding a TV penalization term avoid the presence of oscillary patterns around the edges which may appear when using multiscale methods. We illustrate the results with simulations.

1. INTRODUCTION

New multiscale systems like curvelets [1] and ridgelets [2] are very different from wavelet-like systems. They take the form of basis elements which exhibit very high directional sensitivity and are highly anisotropic. A digital curvelet transform has been proposed in [3, 4] for image denoising and image contrast enhancement. It has been shown [3] that, for denoising problems, the curvelet transform approach outputs a PSNR comparable to that obtained via the undecimated wavelet transform, but the curvelet reconstruction does not contain as many disturbing artifacts along edges that one sees in wavelet reconstructions. Although the results obtained by simply thresholding the curvelet expansion are encouraging, there is of course ample room for further improvement. A quick inspection of the residual images resulting from the *Lena* image filtering for both the wavelet and curvelet transforms shown in paper [5] (figure 5) reveals the presence of very different features. For instance, wavelets do not restore long edges with high fidelity while curvelets are challenged by small features such as *Lena*'s eyes. Loosely speaking, each transform has its own area of expertise and this complementarity may be of great potential.

In [5], a denoising algorithm was proposed which investigates this complementarity, by combining several multiscale transforms in order to achieve very high quality image restoration. Considering K linear transforms $T_1, \dots, T_K$, the method consists of minimizing a functional such as the Total Variation (TV) or the l_1 norm of the multiscale coefficients, but under a set of constraints in the transform domains. Such constraints express the idea that if a significant coefficient is detected by a given transform T_k at a scale j and at a pixel position (x, y), then the transformation of the solution must reproduce the same coefficient value at the same scale and the same position. In short, the constraints guarantee that the reconstruction will take into account any pattern which is detected as significant by any of the K transforms.

Several papers have been recently published, based on the concept of minimizing the total variation under constraints in the wavelet domain [6, 7, 8] or in the curvelet domain [9]. The combined filtering approach [5] can be seen as a generalization of these methods.

Section 2 introduces the deconvolution problem, and discusses different wavelet based methods and section 4 shows how a deconvolution can be derived from a combined approach.

2. WAVELETS AND DECONVOLUTION

Consider an image characterized by its intensity distribution I, corresponding to the observation of a "real image" O through an optical system. If the imaging system is linear and shift-invariant, the relation between the data and the image in the same coordinate frame is a convolution: $I(x, y) = (P * O)(x, y) + N(x, y)$, where P is the point spread function (PSF) of the imaging system, and N is additive noise. We want to determine $O(x, y)$ knowing I and P. This inverse problem has led to a large amount of work, the main difficulties being the existence of: (i) a cut-off frequency of the PSF, and (ii) the additive noise (see for example [10]).

The wavelet based non-iterative algorithm, the wavelet-vaguelette decomposition [11], consists of first applying an inverse filtering ($F = P^{-1} * I + P^{-1} * N = O + Z$ where $\hat{P}^{-1}(\nu) = \frac{1}{\hat{P}(\nu)}$). The noise $Z = P^{-1} * N$ is not white but remains Gaussian. It is amplified when the deconvolution problem is unstable. Then, a wavelet transform is applied on F, the wavelet coefficients are soft or hard thresholded [12], and the inverse wavelet transform furnishes the solution.

The method has been refined by adapting the wavelet basis to the frequency response of the inverse of P [13]. This leads to a special basis, the *Mirror Wavelet Basis*. This basis has a time-frequency tiling structure different from the conventional wavelets one. It isolates the frequency ν_s where $\hat{P}$ is close to zero, because a singularity in $\hat{P}^{-1}(\nu_s)$ influences the noise variance in the wavelet scale corresponding to the frequency band which includes ν_s. Because it may not be possible to isolate all singularities, Neelamani [14] has advocated a hybrid approach, and proposes to still use the Fourier domain to restrict excessive noise amplification. These approaches are fast and competitive compared to linear methods, and the wavelet thresholding removes the Gibbs oscillations. This presents however several drawbacks: (i) the first step (division in the Fourier space by the PSF) cannot always be done properly, (ii) the positivity a priori is not used, and (iii) it is not trivial to consider non-Gaussian noise.

As an alternative, several wavelet-based iterative algorithms have been proposed [15], especially in the astronomical domain where the positivity a priori is known to improve significantly the result. The simplest method consists of first estimating the multiresolution support M (i.e. $M(j, x, y) = 1$ if the wavelet transform of the data presents a significant coefficient at band j and at pixel position (x, y), and 0 otherwise), and to apply the following iterative scheme:

$$O^{n+1} = O^n + P^* * \mathcal{W}^{-1}[M.\mathcal{W}(I - P * O^n)] \quad (1)$$

where $\mathcal{W}$ is the wavelet transform operator. At each iteration, information is extracted from the residual only at scales and positions defined by the multiresolution support. M is estimated from the input data and the correct noise modeling can easily be considered.

3. THE CURVELET TRANSFORM

The Local Ridgelet Transform

The two-dimensional continuous ridgelet transform of a function is defined by:

$$\mathcal{R}_f(a, b, \theta) = \int \overline{\psi}_{a,b,\theta}(x) f(x) dx.$$

where the ridgelet function $\psi_{a,b,\theta}$ is given by

$$\psi_{a,b,\theta}(x) = a^{-1/2} \cdot \psi((x_1 \cos\theta + x_2 \sin\theta - b)/a); \quad (2)$$

with $\int \psi(t)dt = 0$, $a > 0$, $b \in \mathbf{R}$ and each $\theta \in [0, 2\pi)$.

It has been shown [16] that the ridgelet transform is precisely the application of a 1-dimensional wavelet transform to the slices of the Radon transform where the angular variable θ is constant and t is varying.

The ridgelet transform is optimal to find only lines of the size of the image. To detect line segments, a partitioning must be introduced [17]. The image is decomposed into smoothly overlapping blocks of side-length b pixels in such a way that the overlap between two vertically adjacent blocks is a rectangular array of size $b \times b/2$; we use overlap to avoid blocking artifacts. For a $n \times n$ image, we count $2n/b$ such blocks in each direction. The partitioning introduces redundancy, as a pixel belongs to 4 neighboring blocks.

More details on the implementation of the digital ridgelet transform can be found in [3]. The ridgelet transform is therefore optimal to detect lines of a given size, which is the block size.

The Curvelet Transform.

The curvelet transform, proposed by Donoho [18, 1], opens us the possibility to analyses an image with different block sizes, but with a single transform. The idea is to first decompose the image into a set of wavelet bands, and to analyze each band with a local ridgelet transform. The block size can be changed at each scale level. Roughly speaking, different levels of the multi-scale ridgelet pyramid are used to represent different sub-bands of a filter bank output.

The side-length of the localizing windows is doubled *at every other* dyadic sub-band, hence maintaining the fundamental property of the curvelet transform which says that elements of length about $2^{-j/2}$ serve for the analysis and synthesis of the j-th sub-band $[2^j, 2^{j+1}]$. Note also that the coarse description of the image c_J is not processed. We used the default value $B_{min} = 16$ pixels (1.5 arcminute aside per pixel) in our implementation. This implementation of the curvelet transform is also redundant. The redundancy factor is equal to $16J + 1$ whenever J scales are employed.

This method is therefore optimal to detect anisotropic structures of different lengths.

4. THE COMBINED DECONVOLUTION METHOD

Similar to the filtering, we expect that the combination of different transforms can improve the quality of the result. The combined approach for the deconvolution leads to two different methods.

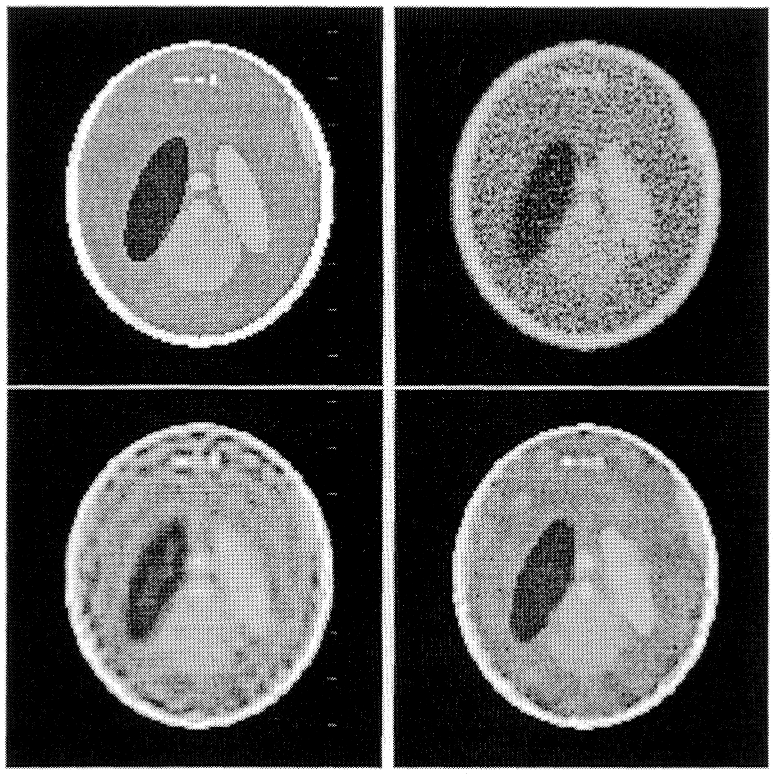

Fig. 1. Top, original image (phantom) and simulated data (i.e. convolved image plus Poisson noise). Bottom, deconvolved image by the wavelet based method and the combined approach.

If the noise is Gaussian and if the division by the PSF in the Fourier space can be carried out properly, then the deconvolution problem becomes a filtering problem where the noise is still Gaussian, but not white. The Combined Filtering Algorithm can then be applied using the curvelet transform and the wavelet transform, but by estimating first the correct thresholds in the different bands of both transforms. Since the mirror wavelet basis is known to produce better results than the wavelet basis, it is recommended to use it instead of the standard undecimated wavelet transform.

An iterative deconvolution method is more general and can always be applied. Furthermore, the correct noise modeling can much more easily be taken into account. This approach consists of detecting, first, all the significant coefficients with all multiscale transforms used. If we use K transforms $T_1, \ldots, T_K$, we derive K multiresolution supports $M_1, \ldots, M_K$ from the input image I using noise modeling.

For instance, in the case of Poisson noise, we apply the Anscombe transform to the data (i.e. $\mathcal{A}(I) = 2\sqrt{I + \frac{3}{8}}$). Then we detect the significant coefficients with the kth transform T_k, assuming Gaussian noise with standard deviation equal to 1, in $T_k\mathcal{A}(I)$ instead of T_kI. $M_k(j, x, y) = 1$ if a coefficient in band j at pixel position (x, y) is detected , and $M_k(j, x, y) = 0$ otherwise. For the band J which corresponds to the smooth array in transforms such as the wavelet or the curvelet transform, we force $M_k(J, x, y) = 1$ for all (x, y).

Following determination of a set of multiresolution supports, we propose to solve the following optimization problem:

$$\min \mathcal{S}(\tilde{O}), \quad \text{subject to} \quad \tilde{O} \in C, \tag{3}$$

where $\mathcal{S}$ is an edge preservation penalization term defined by: $\mathcal{S}(\tilde{O}) = \int \| \nabla \tilde{O} \|_p$, with $p = 1.1$. C is the set of images $\tilde{O}$ which obey the two constraints:

1. $\tilde{O} \geq 0$ (positivity).
2. $M_k T_k I = M_k T_k[P * \tilde{O}]$, for all k.

The second constraint imposes fidelity to the data, or more exactly, to the significant coefficients of the data, obtained by the different transforms. Non-significant (i.e. noisy) coefficients are not taken into account, preventing any noise amplification in the final algorithm.

The solution is computed by using the projected Landweber method [10]:

$$\tilde{O}^{n+1} = \mathcal{P}_c\left[\tilde{O}^n + \alpha(P^* * \bar{R}^n - \lambda\frac{\partial \mathcal{S}(\tilde{O})}{\partial O})\right] \tag{4}$$

where $\mathcal{P}_c$ is the projection operator which enforces the positivity (i.e. set to 0 all negative values). $\bar{R}^n$ is the significant residual which is obtained using the following algorithm:

- Set $I_0^n = I^n = P * \tilde{O}^n$.
- For $k = 1, \ldots, K$ do $I_k^n = I_{k-1}^n + T_k^{-1}\left[M_k(T_k I - T_k I_{k-1}^n)\right]$
- The significant residual $\bar{R}^n$ is obtained by: $\bar{R}^n = I_K^n - I^n$.

α is a convergence parameter and λ is the regularization hyperparameter. Since the noise is controlled by the multiscale transforms, the regularization parameter does not have the same importance as in standard deconvolution methods. A much lower value is enough to remove the artifacts relative to the use of the wavelets and the curvelets. The positivity constraint can be applied at each iteration.

Figure 1, top, shows the Logan-Shepp Phantom and the simulated data, i.e. original image convolved by a Gaussian PSF (full width at half maximum, FWHM=3.2) and Poisson noise. Figure 1, bottom, shows the deconvolution with (left) a pure wavelet deconvolution method (no penalization term) and (right) the combined deconvolution method (parameter $\lambda = 0.4$).

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