Astronomical Data Analysis Software and Systems XXVII
ASP Conference Series, Vol. 522
Pascal Ballester, Jorge Ibsen, Mauricio Solar, and Keith Shortridge, eds.

Multiframe Blind Image Deconvolution using BKWV and TREG Estimators

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Abstract. Accurate information from images can only be extracted if the data is free from noise, and perhaps more importantly - blur. In this study, a technique that renders a sharp version of a scene from multiple blurred frames captured over the same area, is proposed. Each image is assumed to have a different, but unknown, Point Spread Function. Kolmogorov and Moffat kernels that model the atmospheric and ionospheric effects as well as the filtering due to the lens or interferometry, are used. The problem is reduced to a series of iterations in which the blur kernel is initially estimated and subsequently used to deconvolve the input frame. The result is in turn used to update the latent image. A Block based Wavelet-Vaguelet (BKWV) method is adopted to estimate the kernel. In a second step, the algorithm makes use of Tikhonov Regularisation on the spectral domain (TREG) to compute the corresponding global estimate. Encouraging results that are comparable to those achieved by existing approaches, are obtained.

1. Introduction

Rapid advances in sensor technologies and the availability of high performance computing resources, have made the field of astronomy one of the first areas to experience a deluge of information from observations and simulations. Images are said to be ‘sharp’if all objects and details can be perceived clearly. Unfortunately, even the output from very sophisticated instruments is not always of the desired quality. The edge content of the actual scene might not be fully captured and a smoother transition between different intensity levels is recorded. In such cases, the resulting image is said to be blurred. Mathematically, this filtering effect is known as convolution and can be modelled by applying a Point Spread Function (PSF, windowing function, blur filter, or kernel) over the data.

Astronomy is a research area that is predominantly based on remote sensing and imaging. The sources of radiation are not easily (if at all possible) accessible, so new knowledge and results can only be inferred from the recorded signals. Electromagnetic radiation can travel a very long distance in space before reaching our planet. Moreover, turbulence in the atmosphere and the ionosphere layers introduce more distortions in the signals. Different pockets of air create a screen consisting of spatially and temporally varying refractive indices that can strongly aberrate the incoming wavefront (Henry

2012). Therefore, prior to detection, the signal might be diffracted, scattered, and absorbed by different components both external and internal to the instrument (Chromey 2010). While the distortions introduced by the instrument are relatively constant, the filtering due to turbulence in the atmosphere changes in the order of milliseconds (Hirsch et al. 2011).

The objective of this work is to combine two existing single frame non-blind deconvolution estimators to create a multiframe and blind image deconvolution technique. Such a method makes use of a number of images (that show the same subject) captured under different conditions where the PSFs are unknown. Using an iterative technique, complementary information from the given dataset is combined to approximate a single sharp version of the subject. The penultimate goal is to reverse the effects of convolution without knowledge of the filters that were used to blur the images.

2. Restoration through BKWV and TREG

The starting point for this work was the approach suggested by Hirsch et al. (2011). For every frame, the algorithm estimates the PSF (that was used during blurring) and computes an estimate of the original image. The recovered image, referred to the as global estimate or latent image, is refined at every iteration. Since each blurred frame is processed individually, the need for large memory requirements to store all the input images, is avoided. As all the input frames encode the same scene (O), the recorded image I_t at time t (out of a total of T frames) can be mathematically represented by Equation 1.

$$I_t = (O * P_t) + s_t \text{ (for } t = 1, 2, 3, ...T) \tag{1}$$

Here, P_t represents the blur filter at the moment the image is captured and s_t stores the significance of additive non-negative noise.

From a given blurred image and the corresponding PSF, the non-blurred scene can be obtained by the Tikhonov Regularisation on the spectral domain (TREG) technique (Tikhonov et al. 1987; Starck & Murtagh 2006; Fadili et al. 2008). Similarly, once the target scene is known, the PSF can be estimated by the Block based Wavelet-Vaguelet deconvolution (BKWV) method (Chesneau et al. 2010; Fadili et al. 2008).

In the first iteration, the PSF (P_1) is assumed to be a delta function and the global estimate (O_1) is taken to be the input image (I_1). In the second step, the new input image (I_2) together with the current global estimate (O_1) are used to estimate the PSF (P_2). The blurred input image I_2 is then deconvolved with the estimated PSF (P_2) to obtain the deblurred image (O_2). This is in-turn used in the subsequent step. As more images are processed, both estimates are expected to improve. No order of the input images is assumed and an extensively blurred frame can hinder the convergence process resulting in a non-monotonic error decay.

The algorithm goes through a series of epochs by considering each frame more than once. By processing the same set of frames, the accuracy continues to improve. However, for any fixed set of images, there is an upper limit up to which the algorithm can produce better results. This limit primarily depends on the image size to PSF size ratio, the filter type, and the degree of blurring.

Certain observation conditions might result in noise to be introduced in the measured signal. This is generated during the last stages of data capture after the blurring process (Hirsch et al. 2011). The cleaning operation is carried out by considering a number (N) of noisy and blurred images. A median filter is initially applied to each image to minimise strong and inconsistent pixel variations. The data is then transformed to Fourier space and the frequency coefficients are extracted. An average vector is computed and a binary mask (M) that only considers elements with a value equal or greater than one percent of the DC component, is generated. The Fourier space of an image to be cleaned is multiplied by M to eliminate the frequency coefficients introduced by noise.

3. Results

A prototype of the proposed method was implemented and tested on blurred OCNR satellite images convolved with different Kolmogorov kernels. The algorithm was provided with 50 images and was set to complete three epochs. The estimated PSF and the latent image at iterates 1, 2, 5, 20 and 150, are given in Figure 1. The second experiment involved frames of the M31 galaxy blurred with Moffat kernels. Figure 2 shows the results obtained when noise was added to the two images considered. The MSE, correlation, and SNR metrics between the original and the resulting global estimate are presented in Table Table Error Metrics.

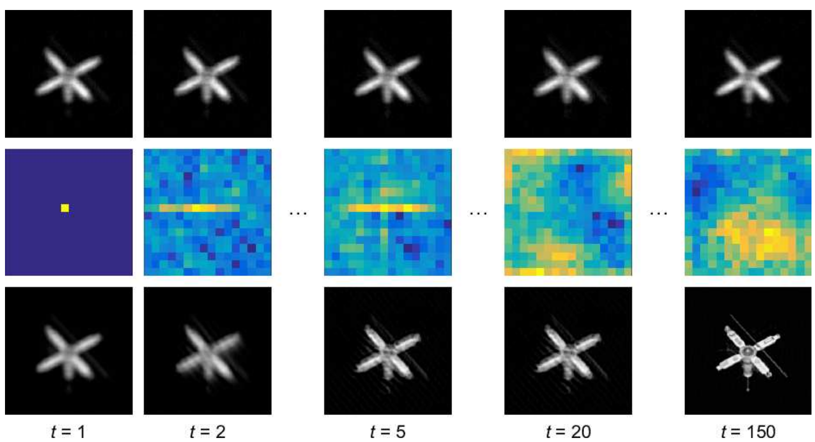

Figure 1. Blurred input images (top row), estimated PSF (middle row), and recovered latent image (bottom row) at different iterates.

Frame SNR		∞	**20.0**	**17.5**	**15.0**	**12.5**	**10.0**
OCNR Sat.	MSE	1.15E-03	2.35E-03	4.72E-03	1.97E-02	6.62E-02	9.69E-02
	COR	0.9858	0.9730	0.9486	0.8682	0.4318	0.3956
	SNR	15.3721	12.2671	9.2294	3.0209	-2.2360	-3.8929
M31 Galaxy	MSE	1.65E-04	3.06E-04	8.30E-04	4.75E-03	8.01E-03	0.0969
	COR	0.9866	0.9757	0.9394	0.7395	0.7350	0.3956
	SNR	15.3954	12.7051	8.3719	0.7906	-1.4733	-3.8929

Table 1. Error metrics for the recovered latent images versus input frame SNR

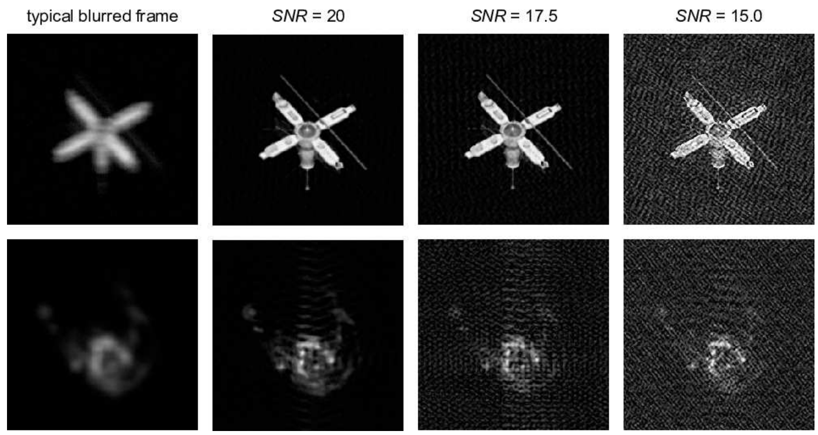

Figure 2. Typical blurred OCNR satellite (top) and M31 galaxy (bottom) frames when datasets with different noise levels were processed.

4. Conclusions and Planned Future Work

The penultimate goal of this study was to develop a multiframe deconvolution technique that takes a number of blurred images and iteratively improves on a global reconstruction. The presented algorithm was tested on sets of images with smooth and extended cosmological sources, as well as detailed patterns. Good results were obtained with very little user involvement. However, the suggested noise cleaning technique proved not to be sufficient to restore images with SNR values below 12.5.

Research on the deblurring of radio images is an ongoing process. Searching through the spaces of possible PSFs and latent images become prohibitively computationally expensive, even for very small raster sets. The technique suggested in this study, uses the available data to direct the search towards a good solution. However, attempts to improve on the accuracy and speed of convergence, further enhance the robustness to noise, as well as minimise the number of required measurements, are still to be made. The possibility of using different error metrics to better evaluate the performance, also leads to further study.

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