Atmospheric Turbulence Effects Removal on Infrared Sequences Degraded by Local Isoplanatism

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Abstract. When observing an object horizontally at a long distance, degradations due to atmospheric turbulence often occur. Different methods have already been tested to get rid of this kind of degradation, especially on infrared sequences. It has been shown that the Wiener filter applied locally on each frame of a sequence allows to obtain good results in terms of edges, while the regularization by the Laplacian operator applied in the same way provides good results in terms of noise removal in uniform areas. In this article, we present hybrid methods which take advantages of both Wiener filter and Laplacian regularization.

1 Introduction

The main perturbation occuring in long distance ground-to-ground video acquisition is due to atmospheric turbulence. The turbulence nature essentially depends on climatic conditions and on the distance between the scene and the camera. The sequence we tested our algorithms on has been provided by *DRDC Valcartier*, Canada, and it was acquired during the NATO RTG40 campaign in New Mexico in 2005. In our sequence acquisition conditions (horizontal observation in the troposphere, at a distance of 1 km), atmospheric perturbation can be efficiently simulated by local blurring and warping and possibly additive noise. Each frame can then be split into mostly regular areas degraded by the same perturbation (*local isoplanatism*).

In our previous work [1], classical restoration methods were adapted for local processing of sequences perturbed by local isoplanatism. We analyzed and compared our results with different criteria, and showed that the Wiener filter allows to obtain good results in terms of visualization (clear edges), while the regularization by the Laplacian operator provides good results for a post-processing (noise removal in uniform areas). In this article, we try to combine the results of these two methods in order to obtain a still better restoration image.

First we briefly recall what local isoplanatism is. Then we explain the general algorithm used to process sequences locally, we show some restoration results and we analyse them. Therefore two new Wiener and Laplacian mixing algorithms are explained and mixing restoration results are shown and analyzed. Finally, a conclusion and perspectives are given.

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2 Local Isoplanatism Theory

Atmospheric turbulence induce varying perturbations on optical beams, according to beams propagation directions. On Fig. 1 is given an example where two beams coming from the same object cross a thin turbulent layer.

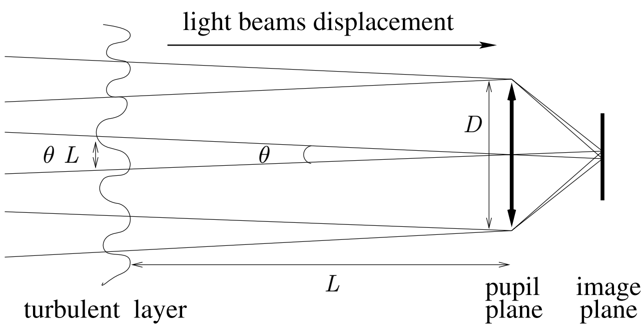


Fig. 1. Origin of different atmospheric perturbations *(θ is the angle between the two beams, L is the distance between the turbulent layer and the pupil, and D is the pupil diameter)*

Three degradation types can occur:

- Anisoplanatism: If $|\theta L| > D$, the turbulent layer areas met by the two beams have no common part. The beams are perturbed by two completely different degradations.
- Local isoplanatism: If the observed object has sufficiently small angular dimensions θ, beams originating from any point on the object and arriving on the pupil can be considered to have encountered almost identical regions of the perturbing layer [2]. That will be translated on the related image by areas with the same degradation.
- Total isoplanatism: When $\theta \approx 0$, the two beams suffer from exactly the same perturbation.

According to [1] and [3], our sequence is degraded by local isoplanatism.

3 Sequence Processing Algorithm and First Restoration Results

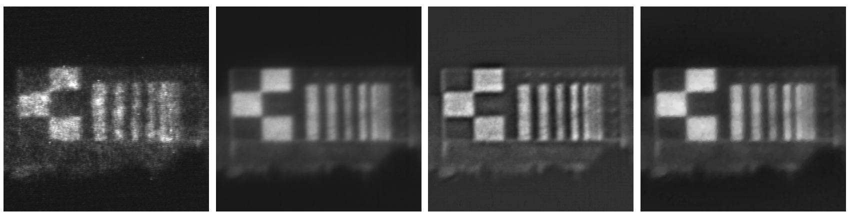
3.1 General Sequence Processing Algorithm

To process a sequence a generalization to different restoration methods of Fraser's and Lambert's algorithm [4] was used. This algorithm was previously tested on simulated images [5]. Its principle is to detect a local space-varying PSF describing the atmospheric turbulence. The PSF is found by using a Wiener filter acting on regions-of-interest of a reference image and each frame of the sequence. The reference image is initially the sequence average and is updated after each deconvolution pass of the complete sequence. The process is repeated until the absolute difference between the two last average images is minimized. In practice, one or two deconvolutions of the complete sequence are sufficient. This algorithm was easily adapted to the case of regularization by the Laplacian [6].

3.2 Local Wiener Filter and Local Laplacien Regularization Results

On Fig. 2 are shown our first restoration results. The processed sequence is compound of 100 frames of 256 x 256 pixels size from an original degraded sequence. It was acquired during night and the object was lighted by a laser. We consider that possible speckle noise is eliminated with spatial integration due to the large target-sensor distance. Looking at Fig. 2, we can observe that averaging allows to strongly decrease noise in the first reference image but the local Laplacian regularization allows to improve noise removal. Also the most suited parameter of the local Wiener filter can be chosen in order to remove the maximum of the remaining blur so as to obtain clearer edges.

We made our processing on MATLAB. Local restoration computing time is from few minutes to about one hour depending essentially on the frame number in the processed sequence, on their size and on regions-of-interest size used to process each frame. 32 x 32 pixels windows were used for local restorations, but the best size to choose is under investigation.



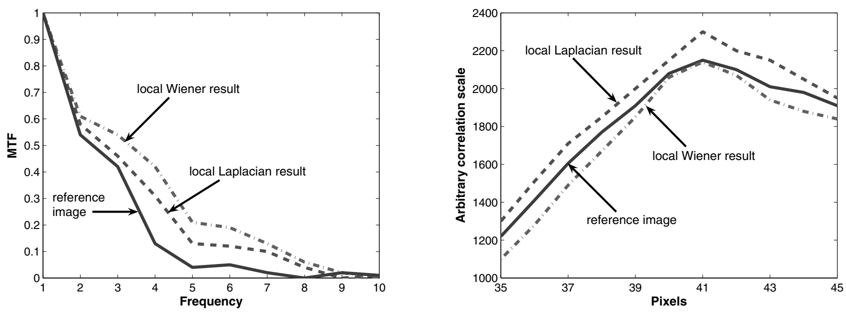
(a) (b) (c) (d)

Fig. 2. First local restoration results on the processed sequence: *(a) Degraded frame, (b) First reference image, (c) Local Wiener result and (d) Local Laplacian result*

3.3 Results Analysis

Like in [1], several criteria have been used to appreciate our restoration results. First mean variances in the three white squares and in the three black squares on the checkerwork were calculated. The best result was obtained with the local Laplacian regularization. Mean slopes of horizontal and vertical transitions between black and white squares were compared: the steepest mean slope was obtained with the local Wiener filter. The modulation transfert function (MTF) of each mean transition between black and white squares was also computed, which provides a quantified and graphic representation of simultaneous qualities of contrast and clearness. The mean transition MTF is the modulus of the Fourier transform of its derivative, and is then normalized to range between 0 and 1. According to Fig. 3(a), the local Wiener filter gives the best MTF. Furthermore for each result, correlations of each mean transition with the ideal one were compared. According to Fig. 3(b), the local Laplacian regularization gives a slightly better result than the local Wiener filter, but this is due to the fact that oscillations are present around each edge on the Wiener result.

To summarize, the local Laplacian regularization allows to improve noise removal on uniform areas whereas the local Wiener filter allows to get rid of a large part of the remaining blur on edges. An hybrid method which will take advantages of these two methods is thereafter presented.



(a) (b)

Fig. 3. First restoration results analysis. *(a) Mean transitions MTFs for the reference image, the local Wiener result and the local Laplacian result. (b) Correlation peaks of the same images mean transitions with the ideal one.*

4 Wiener and Laplacian Mixing Algorithms and Results

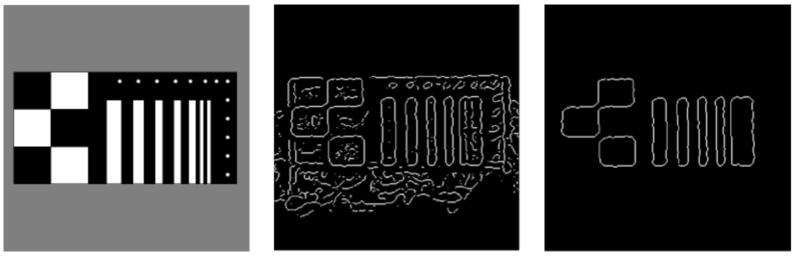
4.1 Segmentation Image

We first need a segmentation image to determine areas where the Wiener result will be kept. It will be obtained with the Canny-Deriche filter. To limit false edge detection, we use the three images we have in input: the reference image, the local Wiener result and the local Laplacian result. On the final segmentation image, an edge point is kept only if it's present on at least two of the three used segmentation images.

Two segmentation thresholds (*thr*) have been chosen: the first one allows to detect small white circles above and on the right of vertical bars (Fig. 4(b)), while the second one allows to obtain a "clean" segmentation (Fig. 4(c)).

4.2 Wiener and Laplacian Mixing (WLM) Algorithms

In the first version of Wiener and Laplacian Mixing (called *WLM1*), the area where we apply the result of the local Wiener filter is compound of edge points



(a) (b) (c)

Fig. 4. Observed objet *(a)* and the 2 used segmentation images: *(b) thr=0.04 and (c) thr=0.35*

and a thickness of several pixels around them, estimated according to the pixel number needed for the local Wiener mean transition. Everywhere else is applied the result of the local Laplacian regularization (Fig. 5). WLM1 results are shown on Figs. 6(a) and 6(b).

In the second version of WLM (named *WLM2*), we use a gradation to pass from the Wiener result to the Laplacian result in order to attenuate the small gray level difference between Wiener and Laplacian results. We add weighting coefficients in front of each result according to the closeness/distance of the current pixel from the nearest edge point. For each pixel, we use the following formula:

$$\forall i, j, WLM2(i,j) = \alpha_1(c)LWR(i,j) + \alpha_2(c)LLR(i,j) , \qquad (1)$$

where *WLM2* is the WLM2 result, *LWR* is the local Wiener result, *LLR* is the local Laplacian result, c is the distance card obtained from the segmentation image and representing the distance between each pixel and the nearest edge point, and α_1 and α_2 are defined using the three following conditions:

$$\alpha_1(c) + \alpha_2(c) = 1 \; , \; 0 \le \alpha_1(c) \le 1 \; , \; 0 \le \alpha_2(c) \le 1 \; . \qquad (2)$$

The closer to an edge point, the higher α_1 and the lower α_2, and conversely. Once again, the gradation is made on several pixels from the center of the local Wiener mean transition, according to the pixel number needed for this mean transition (Fig. 5). WLM2 results are shown on Figs. 6(c) and 6(d).

4.3 Results Analysis

Analysis of our results have been realized with the same criteria than those previously used, and similar results to previous ones have been found (Fig. 7): WLM results mean transitions provide MTFs almost as good as those obtained with the local Wiener result, and correlation peak with the ideal transition has been improved compared with the local Wiener result. Moreover the Canny-Deriche filter has been tried on our restoration results, which allows us to conclude that

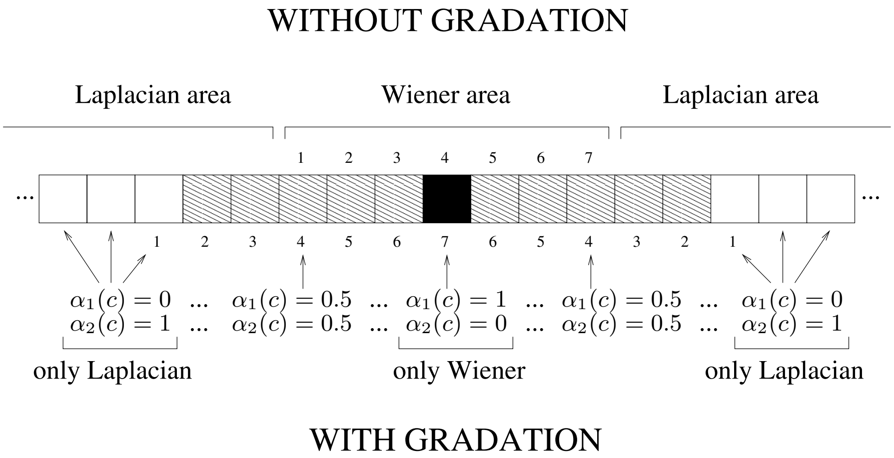


Fig. 5. Processing areas determination. *Top: division (without gradation). Bottom: overlaying (with gradation).*

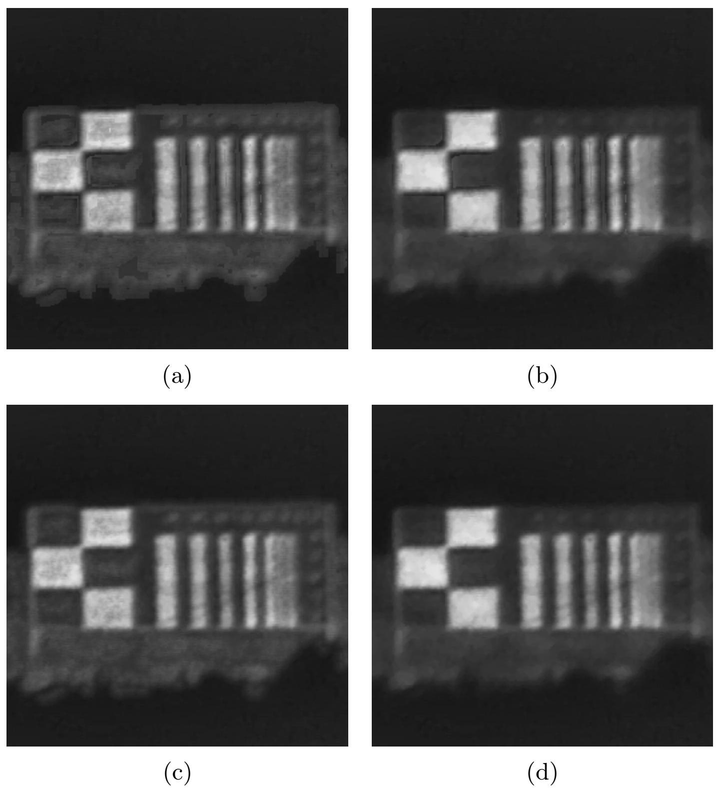
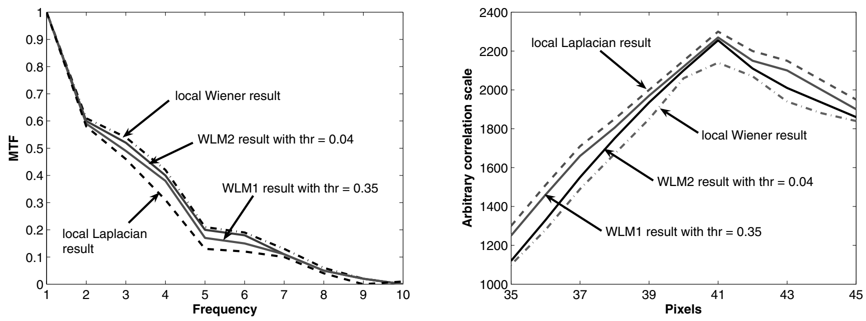


Fig. 6. WLM1 results with *thr=0.04 (a)* and *thr=0.35 (b)*. WLM2 results with *thr=0.04 (c)* and *thr=0.35 (d)*.

gradation use allows to slightly decrease false edges detection, and that white circles are better detected on the WLM2 result with low threshold. Horizontal cuts have also been realized along small white circles above the vertical bars (Fig. 8). Results strongly depend on the chosen segmentation threshold since if circles are not detected on the segmentation image used for the WLM algorithms, the Laplacian result is applied and edges are smoothed. We can note that the WLM2 algorithm with low threshold gives best results in average: the gray level difference between circles and the object background is larger.



(a) (b)

Fig. 7. WLM restoration results analysis. *(a) Mean transitions MTFs. (b) Correlation peaks with the ideal transition.*

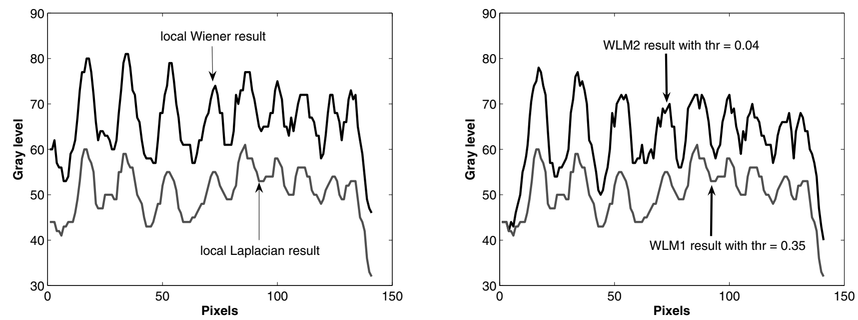


Fig. 8. Horizontal cuts along white circles

5 Conclusion and Perspectives

According to our previous restoration work, the local Laplacian regularization allows to improve noise removal on uniform areas, and a judicious choice of the local Wiener filter parameter allows to get rid of a large part of the remaining blur on edges. These two methods results have then been mixed in order to obtain a still better restoration result. The new algorithms results strongly depend on the segmentation image. The smaller the segmentation threshold, the more detected false edges and the more noisy uniform areas. Nevertheless with a small segmentation threshold and in spite of a certain noise, we managed to better detect white circles than previously. Furthermore gradation between Laplacian and Wiener areas allows to decrease gray level difference, and then to improve the result for both vizualisation and post-processing.

We are currently studying regions-of-interest size influence on restoration results quality. Automatic selection of segmentation threshold is also under investigation, with a method based on detected edge points number study, which could improve our restoration methods especially on textured areas.

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