FILTERING OF FLUID IN MOTION IMAGES USING OPTIMAL MESH SMOOTHING

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1. INTRODUCTION

Due to the significant amount of noise in Sea Surface Temperature (SST) images that originate from different atmospheric sources and the sensor itself, current detection methods detect false fronts or neglect to detect fronts. Various methods have been used to filter the SST images including low-pass filter [1], contextual filter [2], adaptive filtering [3] and others [4]. The present paper introduces the optimal meshed smoothing approach [5] for SST images and validates the efficiency of the method on synthetic images of fluid in motion.

2. OPTIMISATION-BASED APPROACH TO MESH SMOOTHING

2.1 General Framework

Hamam and Couprie showed in [5] that mesh smoothing may be reformulated as a minimisation of the cost function J as defined below:

$$J = \frac{1}{2}[(x-\hat{x})^t Q(x-\hat{x}) + \theta_0 x^t x + \theta_1 x^t \bar{A} x + \theta_2 x^t \bar{A}^2 x] \tag{1}$$

where

- Q is a symmetric positive definite weighing matrix,
- θ_0, θ_1 and θ_2 are weighing scalars,
- $\bar{A} = C^t \Omega C$, and Ω is a diagonal matrix of weight associated to each edge,
- C is the node-edge matrix of the image.
- x and $\hat{x}$ are respectivly the coordinates of the nodes and their initial coordinates.

The inclusion of initial values in the cost function prevents the smoothing from shrinking the object.

For large size problem, a gradient descent algorithm may be used to minimise J and the convergence is guaranteed.

2.2 Second Order algorithm With Attach (SOWA)

Eq.2 represents a special case of the cost function J defined in Eq.1. In the SOWA algorithm, the cost function J can be expressed as follows:

$$J = \frac{1}{2}[(x - \hat{x})^t(x - \hat{x}) + \theta x^t \bar{A}^2 x]. \tag{2}$$

For small size problem, the solution can be found by matrix inversion,

$$x = (I + \theta \bar{A}^2)^{-1}\hat{x}, \tag{3}$$

and the solution is unique.

For large size problems, the gradient descent method may be applied. One iteration of the gradient descent method is as follows:

$$x^{n+1} = x^n - \alpha^n \nabla_x J = x^n - \alpha^n[(x^n - \hat{x}) + \theta \bar{A}^2 x^n], \tag{4}$$

where

- α^n is the step at the n^{th} iteration
- $\nabla_x J$ is the gradient of J

The optimal step for the gradient descent is given by:

$$\alpha^n = \frac{\nabla_x J^t \nabla_x J}{\nabla_x J^t (I + \theta \bar{A}^2) \nabla_x J} \tag{5}$$

The SOWA method is chosen when the smoothing needs to conserve the curves of the image.

3. SIMULATIONS

The SOWA method has been run on synthetic images of fluids in motion. The convergence of the algorithm has been tested for various values of θ (Fig.1).

Fig1. shows that the SOWA algorithm converges towards the solution in approximately 15 iterations. Fig3. and Fig4. depict the results of the SOWA algorithm and compare them to the output of the Wiener filter. It may be clearly noticed that in both cases (Gaussian and Speckle noise), the SOWA algorithm outperforms the Wiener filtering in terms of curve definition and homogeneity. Fig5. and Fig6. show the result of the smoothing on real SST images.

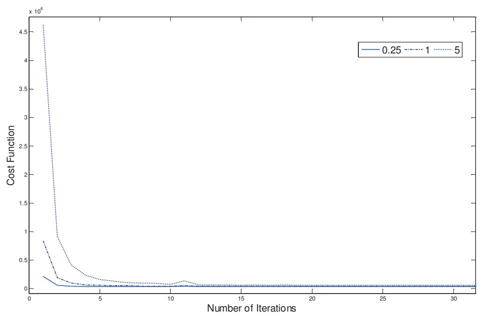

Figure 1: Convergence of SOWA with various values of θ

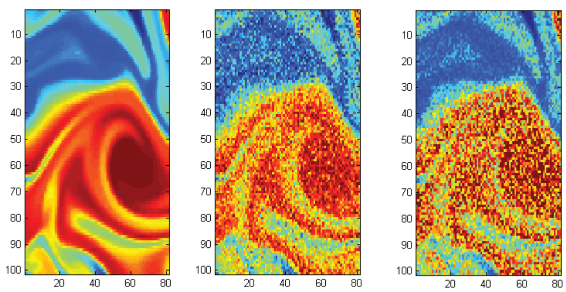

Figure 2: a) Initial image b) Image with Gaussian noise ($\mathrm{m} = 0$ and $\sigma^2 = 0.01$) c) Image with Speckle noise ($\mathrm{m} = 0$ and $\sigma^2 = 0.04$)

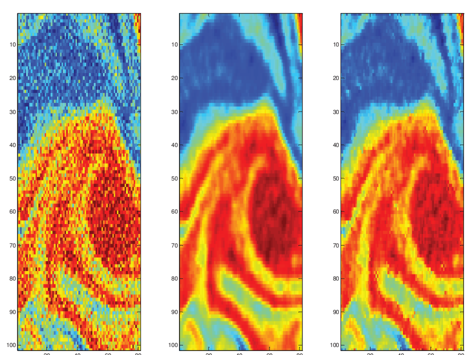

Figure 3: a) Noisy image (Gaussian noise) b) Image after smoothing ($\theta = 1$) c) Filtered image using the Wiener filter

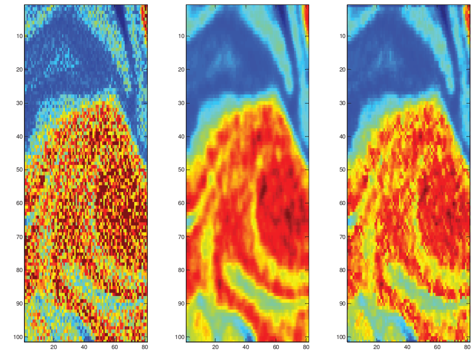

Figure 4: a) Noisy image (speckle noise) b) Image after smoothing ($\theta = 1$) c) Filtered image using the Wiener filter

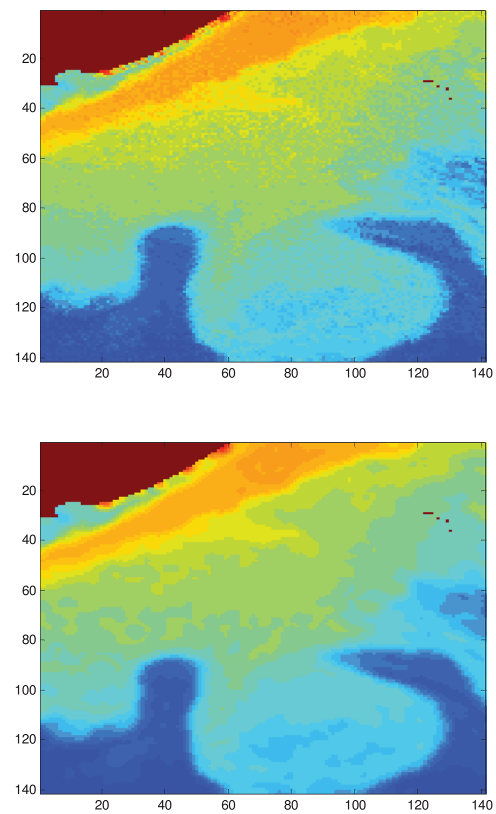

Figure 5: a) SST image detail b) Result of the smoothing.

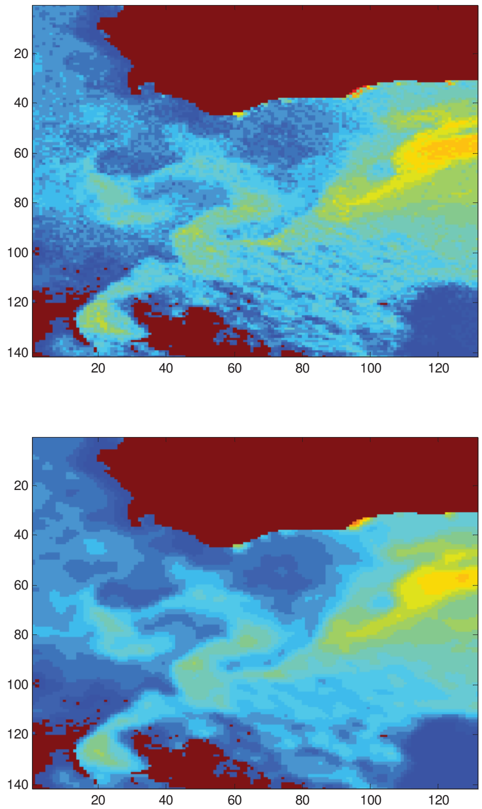

Figure 6: a) SST image detail b) Result of the smoothing.

4. CONCLUSION AND FUTURE WORKS

Simulation has shown that the SOWA algorithm gives very good results in removing Gaussian and Speckle noise on the synthetic images. Future work will focus on the sub-sampling of images to improve the contrast of the Sea Surface Temperature (SST) images.

5. REFERENCES

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