SHIP WAKE DETECTION FOR SAR IMAGES WITH COMPLEX BACKGROUNDS BASED ON MORPHOLOGICAL DICTIONARY LEARNING

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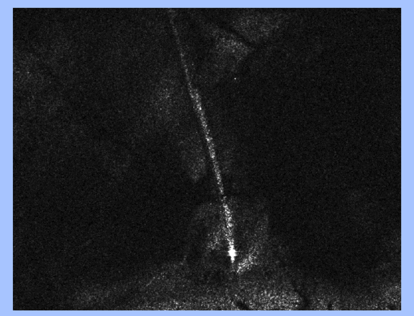
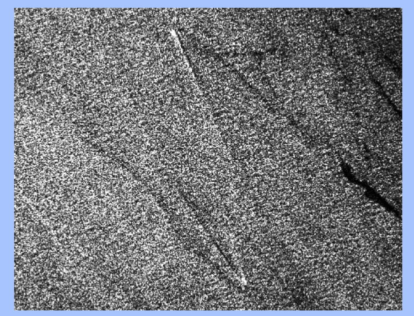
Introduction

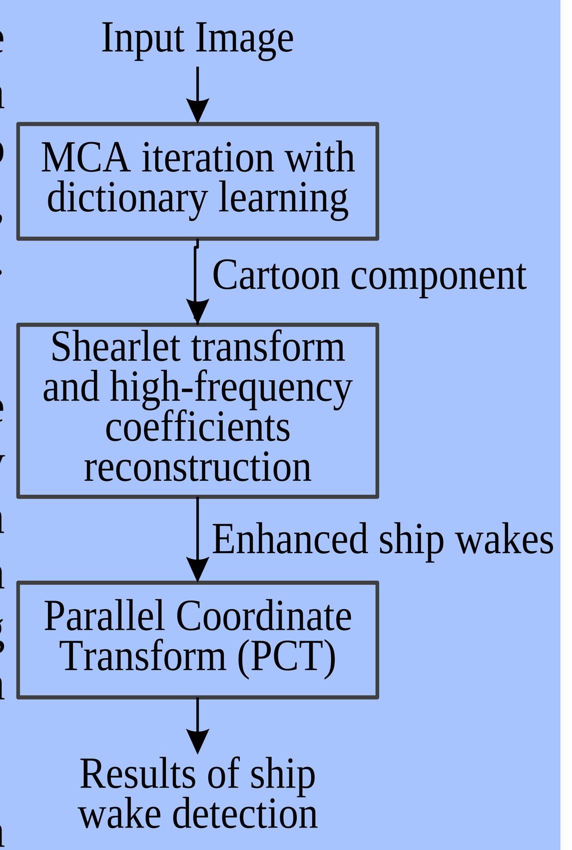
- Ship wake detection is greatly useful not only for estimating the speed and the direction of moving ships, but also for finding small ships which are hard to be detected [1].
- Related work dates from late 1980s, much of which uses the Radon transform or the Hough transform after speckle noises are reduced.
- Traditional ship wake detection methods can only work well under simple background conditions, but fail under complex background conditions.
- we propose a novel ship wake detection method based on the morphological component analysis (MCA) and the dictionary learning for complex backgrounds.


Simple background


Complex background

The Proposed Method

- The ship wake SAR image $\mathbf{X}$ can be regarded as a superposition of a cartoon component $\mathbf{S}$ containing ship wakes, a sea texture component $\mathbf{T}$, and a residual $\mathbf{R}$ with speckle noises. That is $\mathbf{X}=\mathbf{S}+\mathbf{T}+\mathbf{R}$.
- Ship wakes will be extracted from the separated cartoon component $\mathbf{S}$ by using MCA, and the detection capability of ship wakes in the cartoon component will be improved by using dictionary learning to separate $\mathbf{S}$ from $\mathbf{T}$ and $\mathbf{R}$.
- Flow chart of our method is shown on the right.



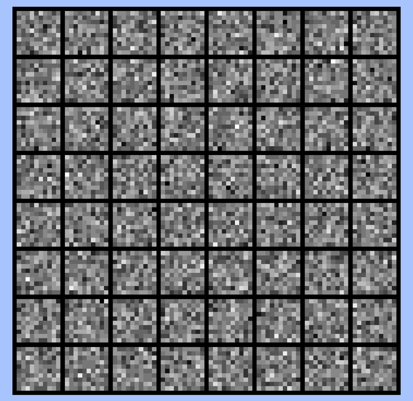
MCA-based Cartoon Component Separation

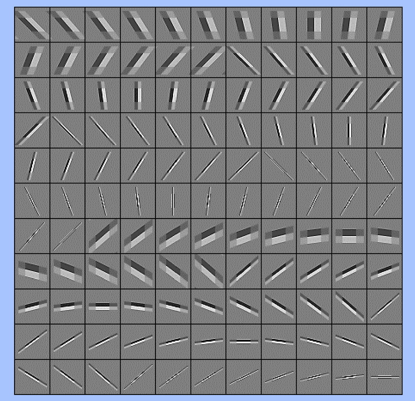
- According to the MCA, the separation of the cartoon component and the texture component can be expressed as follows:

$$\min_{\mathbf{S},\mathbf{T}}\left(\sum_{i=1}^{M}\|\boldsymbol{\alpha}_{\mathbf{S},i}\|_1+\sum_{j=1}^{N}\|\boldsymbol{\alpha}_{\mathbf{T},j}\|_1+\gamma\|\mathbf{S}\|_{\mathrm{TV}}\right)$$
$$\text{s.t. } \|\mathbf{X}-\mathbf{S}-\mathbf{T}\|_2\le\epsilon$$

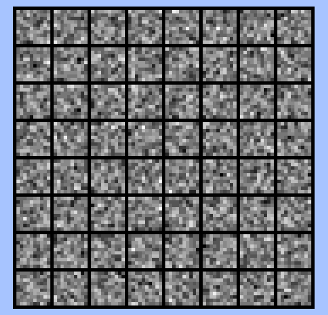
where, $\boldsymbol{\alpha}_{\mathbf{S},i}$ and $\boldsymbol{\alpha}_{\mathbf{T},j}$ are the ith and the jth block-SRC of $\mathbf{S}$ and $\mathbf{T}$ respectively, $\|\mathbf{S}\|_{\mathrm{TV}}$ is the total variation term to keep $\mathbf{S}$ more smooth, γ is a regularization coefficient, and ϵ is the residual.

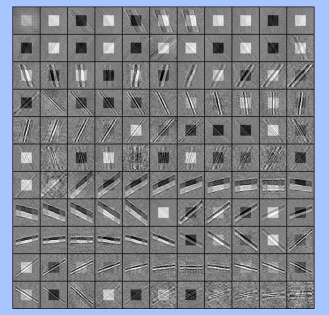
- The sea texture dictionary $\mathbf{\Phi_T}$ is initially random to represent the complexity of sea clutter, and the atom size of this dictionary is 10×10 with total number 64.
- The ship wake dictionary $\mathbf{\Phi_S}$ is initially from a 4-layer with18 direction in each layer shearlet transform, and the atom size of this dictionary is 20×20 with total number 64.


Initial dictionary of sea texture

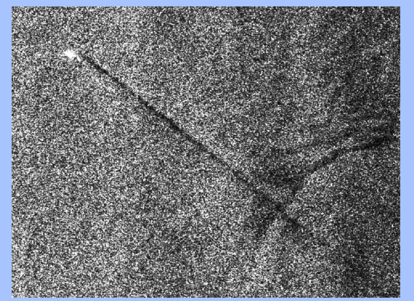

Initial dictionary of ship wake

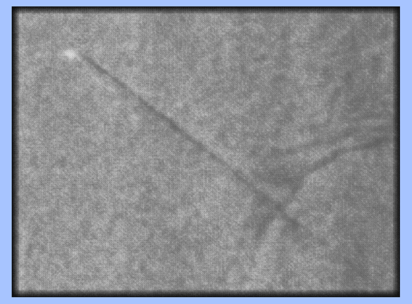
- With the block coordinate descent (BCD) dictionary learning method, the initial $\mathbf{\Phi_T}$ and $\mathbf{\Phi_S}$ are refined. The final dictionaries are as follows:

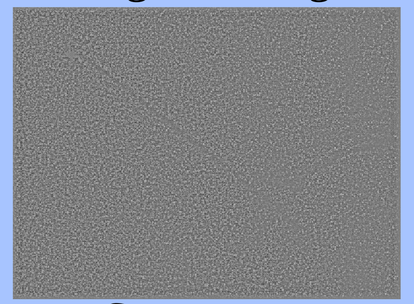

Final sea texture dictionary

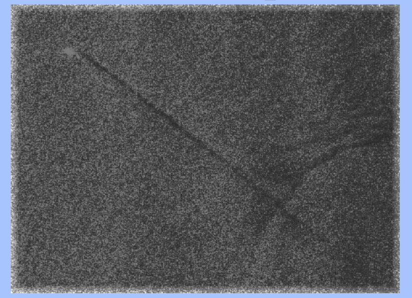

Final ship wake dictionary

- The refined dictionaries are used for next iteration, MCA parameters are set empirically, the cartoon component will be finally separated.


Original image

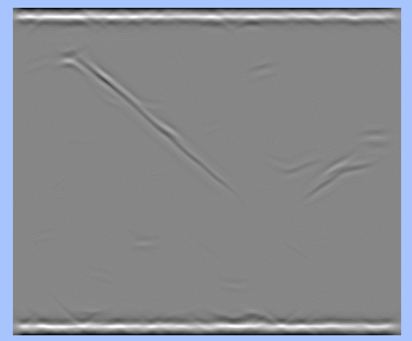

Cartoon component

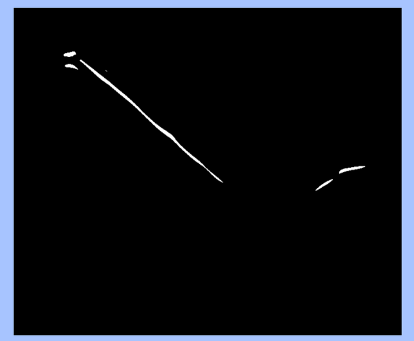

Sea texture


The residual

Shearlet Transform-based Cartoon Component Enhancement

- Ship wakes in the cartoon component exhibit directional high-frequency characteristics, and shearlet basis functions can respond to them.
- Ship wakes will be enhanced by extracting some shearlet high-frequency coefficients of the cartoon component and reconstructing some important ones, and then binarized to get a clean ship wake image.

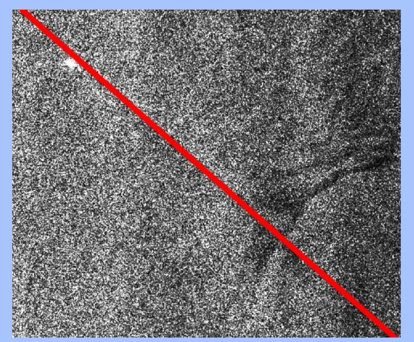

Reconstructed cartoon component


Binary image of the reconstructed one

PCT-based Line Detection

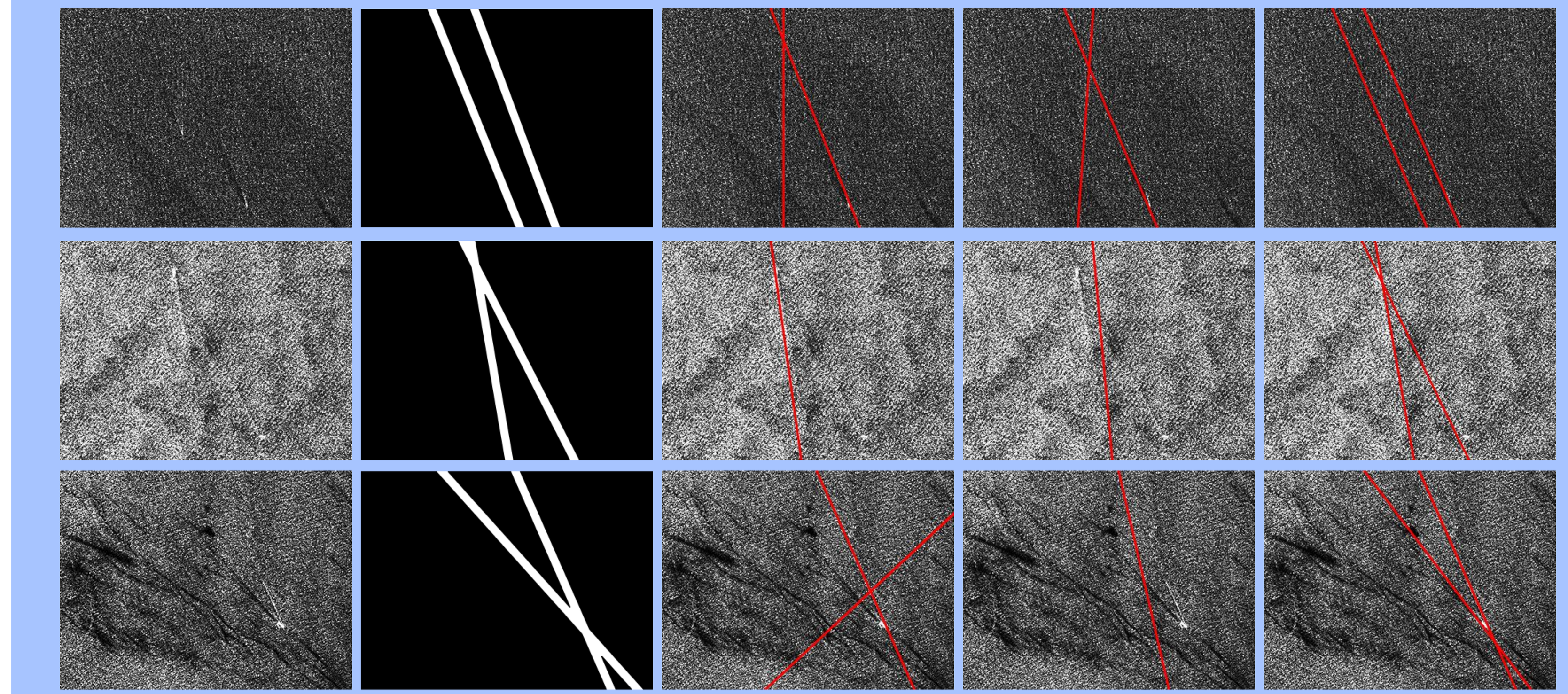
- A point in the image is converted into a line in the parallel coordinate system (PCS). All points lying in the same straight line will intersects at a point in the PCS.
- The points in the PCS with extreme values will be extracted and remapped back to the image as the lines representing the ship wakes.


PCT of the binary reconstructed image


Inverse PCT and overlay with the input

Results

- 21 ERS-2 images are used to evaluate the performance of the proposed method, and results are compared quantitatively and qualitatively with those of [2] and [3].
- In qualitative comparison, detection results of the related methods corresponding to the optimal Recall and Precision are partly demonstrated as the follows.


Original image Ground truth Results of [2] Results of [3] Our results

- In quantitative evaluation, the Recall and the Precision values are calculated, and the largest one of these values in bold means the best performance of corresponding method.

	Ref [2]	Ref [3]	**Our method**
Recall	0.41	0.22	**0.72**
Precision	0.39	0.24	**0.70**

Conclusions

- A novel ship wake detection method based on MCA and dictionary learning for complex backgrounds is proposed in this paper.
- Our method include the following features:

—Ship wakes in cartoon component are separated from the complex sea background texture component.

—Ship wakes are enhanced by reconstructing some high-frequency shearlet coefficients of the cartoon.

—Finally, ship wakes are detected by the parallel coordinate transform.

References

[1] M.T. Rey, et al, “Application of radon transform techniques to wake detection in seasat-a sar images”, IEEE TGRS, 28(4):553–560, 1990.

[2] J.Ai, et al, “A novel ship wake CFAR detection algorithm based on SCR enhancement and normalized hough transform”, IEEE GRSL, 8(4):681–685, 2011.

[3] X.Xing, *et al*, “An enhancing normalized radon transform method for ship wake detection in SAR imagery”, EUSAR 2012, Nuremberg, Germany, pp.559–562, 2012.