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Extraction and Analysis of RFI Signatures via Deep Convolutional RPCA

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Abstract

Radio Frequency Interference (RFI) poses a significant threat to microwave remote sensing instruments like synthetic aperture radar (SAR), which causes information loss, image degradation and reduces measurement accuracy. In this paper, considering the temporal-spatial correlation of target response, and the random sparsity property for time-varying interference, we propose a novel approach for mitigating RFI signals in SAR raw data utilizing the joint low-rank and sparse property. Instead of applying the iterative optimization process with uncertain computation burden, the proposed Deep Convolutional RPCA approximates the iterative process with a stacked recurrent neural network. It employs the supervised deep learning to speed up the efficiency and adjusts the hyperparameters adaptively. The experimental results show that the validity of the proposed method.

1 Introduction

Synthetic aperture radar (SAR) is an important active instrument for remote sensing, which have been widely applied in a multitude of applications, ranging from earth observation, natural hazards management, marine coastal ocean monitoring as well as security-related applications. SAR systems must share the frequency spectrum with other radio services, and thus electromagnetic signals from other radio emitters are often present to varying degrees, which is referred to as radio frequency interference (RFI) [1].

The RFI issues have drawn great attention in recent years due to its adverse impact on SAR data, ranging from image formation process, image interpretation, as well as the accuracy of post-processing interferometric or polarimetric products [2]. Therefore, a lot of efforts has been devoted and various mitigation techniques have been proposed to mitigate the adverse impact to SAR products. Tao *et al.* provides a thorough review of state-of-art techniques in [3]. The sensitivity of a given sensor to RFI is correlated with the specific nature of the RFI experienced, and the global heterogenous interference environments make it difficult to characterize the RFI problem. Therefore, it is worth noting that there is no universal scheme that capable for dealing with all various RFI scenarios.

One kind of mitigation techniques uses the idea of signal decomposition, which manages to extract the latent components or subspaces corresponding to RFI according to feature difference between RFI and target echoes, including the power, statistical difference, etc. Among them, the sparse and low rank property are well demonstrated in [4]-[7] by employing the robust principal component analysis (RPCA). The RPCA approach can decompose the data matrix into a low rank component and a sparse component via unsupervised iterative optimization. However, its efficiency is limited because of the relatively large dimension of the data matrix. Meanwhile, the hyperparameters should be determined as a prior, which is not a simple task in practical applications due to lack of prior information about RFI.

On the other hand, with the advancement of artificial intelligence, several neural network-based learning methods for RFI mitigation in SAR system have shown superior performance and promising potential [8]. The *universal approximation theorem* states that a feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets. By substituting each iteration of an iterative algorithm as a layer in a deep neural network and then concatenating few such layers, Gregor *et al.* [9] showed that it is possible to achieve a dramatic improvement in convergence.

Therefore, motivated by the work in ultrasound imaging in [10], we proposed a modified framework for RFI mitigation in SAR data via Deep Convolutional RPCA. It transforms the original unsupervised decomposition problem into a supervised neural network-based learning problem. By this transform, the number of iterations is reduced significantly and the hyperparameters is also learned from the data without manual setting. This provides a new insight about previous iterative optimization problems like RPCA.

2 Problem Formulation

Without loss of generality, the discretized radar echoes could be modelled as a mixture of target echoes, interferences, and thermal noise, i.e.,

$$e(n) = x(n) + rfi(n) + noise(n) \tag{1}$$

where $x(n)$, $rfi(n)$, $noise(n)$ denotes the target echoes, RFI and additive Gaussian noise, respectively.

Since RFI and target response are originated from different sources, the frequency information evolving with time is different. It is straightforward to characterize the RFI

signatures in time-frequency plane. The short time frequency transform (STFT) is an efficient yet effective method, which can be represented as,

$$\mathbf{Y} = \sum_{m=0}^{M-1} h(m)x(n+m)e^{-j2\pi mk/M} \tag{2}$$

where $\mathbf{Y}$ is the resulting STFT spectrogram for each azimuth pulse, and $h(m)$ is a sliding window with length of M.

After acquiring N_a azimuth pulses, and stacking the STFT spectrograms as vectors in a matrix, the RFI-contaminated echoes $\mathbf{D} \in \mathbb{C}^{PQ\times N_a}$ can be expressed as,

$$\mathbf{D} = \mathbf{L} + \mathbf{S} + \mathbf{N} \tag{3}$$

where $\mathbf{L} \in \mathbb{C}^{PQ\times N_a}$ is assumed as a low-rank matrix corresponding to the target response because of its high temporal-spatial correlation. $\mathbf{S} \in \mathbb{C}^{PQ\times N_a}$ is assumed as a sparse matrix corresponding to the interference, since it appears randomly and sparsely on the 2-D data plane [5].

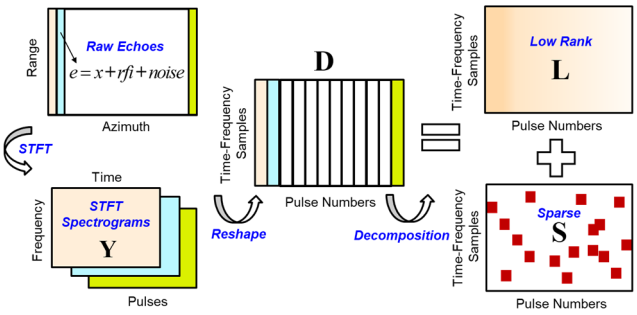


Figure 1. Representation of joint low-rank and sparse model for SAR data.

More generally, Eq. (3) could be formulated as,

$$\mathbf{D} = \mathbf{H}_1\mathbf{L} + \mathbf{H}_2\mathbf{S} + \mathbf{N} \tag{4}$$

where $\mathbf{H}_1$ and $\mathbf{H}_2$ are the measurement matrices of appropriate dimensions, which relate the measurements to the unknown quantities we wish to recover. In this application, $\mathbf{H}_1 = \mathbf{H}_2 = \mathbf{I}$ are identity matrices.

For RFI mitigation, the goal is managed to extract the latent $\mathbf{L}$ and $\mathbf{S}$ from $\mathbf{D}$ utilizing the joint low-rank and sparse property, which is a minimization problem,

$$\min_{\mathbf{L},\ \mathbf{S}} \ \frac{1}{2}\left\|\mathbf{D} - (\mathbf{H}_1\mathbf{L} + \mathbf{H}_2\mathbf{S})\right\|_F^2 + \lambda_1\|\mathbf{L}\|_* + \lambda_2\|\mathbf{S}\|_{1,2} \tag{5}$$

where $\|\cdot\|_*$ denotes the nuclear norm and $\|\cdot\|_{1,2}$ denotes the mixed $l_{1,2}$ norm.

Further, Eq. (5) can be rewritten as

$$\min_{\mathbf{L},\ \mathbf{S}} \ \frac{1}{2}\|\mathbf{D} - \mathbf{A}\mathbf{X}\|_F^2 + h(\mathbf{X}) \tag{6}$$

where $\mathbf{X} = [\mathbf{L};\mathbf{S}]$, $\mathbf{P}_1 = [\mathbf{I};\mathbf{0}]$, $\mathbf{P}_2 = [\mathbf{0};\mathbf{I}]$, and $h(\mathbf{X}) = \sum_{i=1}^{2} \lambda_i \rho_i(\mathbf{P}_i\mathbf{X})$, $\rho_1 = \|\bullet\|_*$, $\rho_2 = \|\bullet\|_{1,2}$.

The minimization problem is a regularized least-squares problem, and one solution is via fast iterative shrinkage/thresholding algorithm (FISTA) [10],

$$\mathbf{L}^{k+1} = \mathrm{SVT}_{\lambda_1/L_f}\left\{\left(\mathbf{I} - \frac{1}{L_f}\mathbf{H}_1^H\mathbf{H}_1\right)\mathbf{L}^k - \mathbf{H}_1^H\mathbf{H}_2\mathbf{S}^k + \mathbf{H}_1^H\mathbf{D}\right\} \tag{7}$$

$$\mathbf{S}^{k+1} = T_{\lambda_2/L_f}\left\{\left(\mathbf{I} - \frac{1}{L_f}\mathbf{H}_2^H\mathbf{H}_2\right)\mathbf{S}^k - \mathbf{H}_2^H\mathbf{H}_1\mathbf{L}^k + \mathbf{H}_2^H\mathbf{D}\right\} \tag{8}$$

where $\mathrm{T}_\alpha(\mathbf{X}) = \max\left(0, 1 - \alpha/\|\mathbf{x}\|_2\right)\mathbf{x}$ and $\mathrm{SVT}_\alpha(\mathbf{X})$ is the soft-thresholding and singular value thresholding operator. The iterative process is data-driven optimization, and the performance depends on the empirically choice of hyperparameters λ_1 and λ_2.

3 Convolutional RPCA

In this part, we introduce the recurrent neural network to reformulate the iterative problem in (7)-(8), in which a iteration step can be substituted by a network layer. The matrix multiplications in (7)-(8) can be replaced by convolutional layers, as defined [10],

$$\mathbf{L}^{k+1} = \mathrm{SVT}_{\lambda_1^k}\left\{\mathbf{P}_5^k * \mathbf{L}^k + \mathbf{P}_3^k * \mathbf{S}^k + \mathbf{P}_1^k * \mathbf{D}\right\} \tag{9}$$

$$\mathbf{S}^{k+1} = \mathrm{T}_{\lambda_2^k}\left\{\mathbf{P}_6^k * \mathbf{L}^k + \mathbf{P}_4^k * \mathbf{S}^k + \mathbf{P}_2^k * \mathbf{D}\right\} \tag{10}$$

where $*$ is the convolution operator. $\mathbf{P}_1^k, \cdots, \mathbf{P}_6^k$ denote the convolutional kernels of the k-th layer that learned from the training data. The convolutional RPCA is trained using back-propagation method and the loss function is chosen as the sum of the mean squared errors between the predicted values,

$$Loss(\vartheta) = \frac{1}{2N}\left(\sum_{i=1}^{N}\left\|f_S(\mathbf{D}_i, \vartheta) - \hat{\mathbf{S}}_i\right\|_F^2 + \sum_{i=1}^{N}\left\|f_L(\mathbf{D}_i, \vartheta) - \hat{\mathbf{L}}_i\right\|_F^2\right) \tag{11}$$

where $\mathbf{D}_i$, $\hat{\mathbf{S}}_i$, $\hat{\mathbf{L}}_i$ are the training samples. N is the number of samples. $f_S(\mathbf{D}_i, \vartheta)$ and $f_L(\mathbf{D}_i, \vartheta)$ is the estimated sparse, low-rank components that determined by the parameter set $\vartheta = \{\mathbf{P}_1^k, \cdots, \mathbf{P}_6^k, \lambda_1^k, \lambda_2^k\}$. Equivalently, the original unsupervised data-oriented iterative optimization problem is transformed to a supervised learning problem corresponds using a stacked recurrent neural network.

4 Experimental Results and Discussions

In this part, the performance is verified by a simulated experiment. An airborne SAR dataset operates at X-band is used for illustration. Several representative RFI signals that easily encountered in real scenarios [3], i.e., narrow-band signals, pulsed signals, wide-band signals, are artificially simulated and injected on the raw data echoes.

The number of samples along range dimension is 4096. Considering the relatively large dimension and to alleviate the computation burden of training process, the entire 2-D data is cropped into small pieces of size, as shown in Figure 2. Totally 2000 matrix samples are used for training, and 560 samples are used for test.

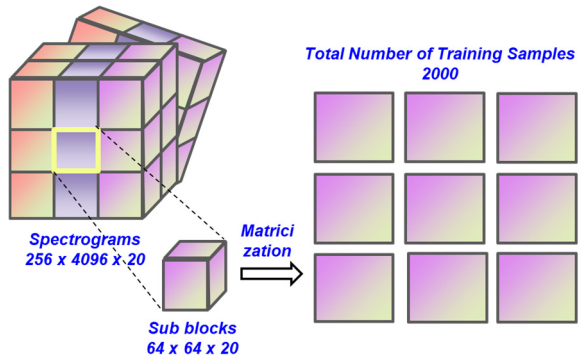


Figure 2. Schematic of the sub-blocks division for training.

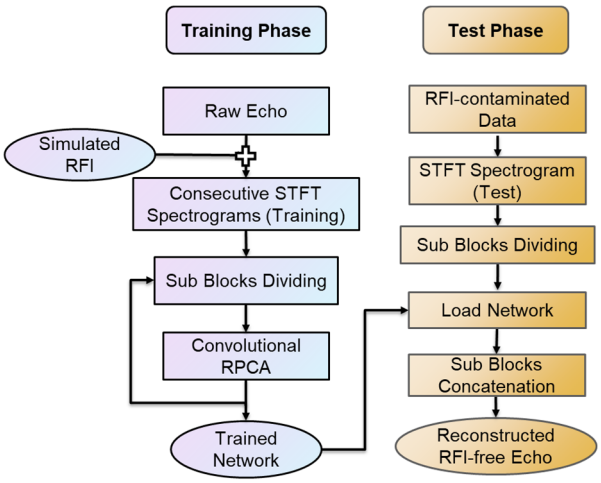


Figure 3. Flowchart of the proposed method.

The convolutional RPCA has 10 layers. The first three layers use convolution kernels of size 5×5×1, while the last seven layers use filters of size 3×3×1. The learning process is accomplished by the Adam optimizer with a learning rate of 0.002. Figure 3 summarizes the flowchart of the proposed method. With the convergence of the training process, the well-trained network is loaded for test. In the test phase, the data is also divided into small sub-blocks and undergoes a concatenation step after applying the proposed scheme.

Figure 4 shows the variation of loss function with iteration steps in the training phase. It shows the training loss is gradually decreased, and undergoes slight fluctuations after 50 epochs.

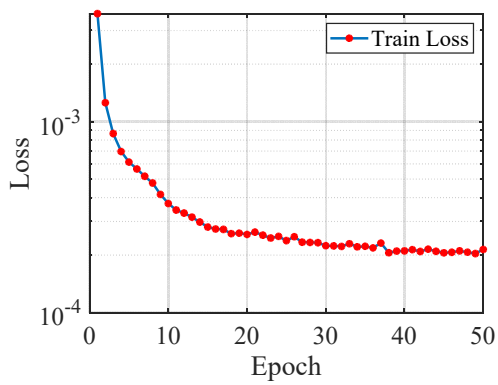
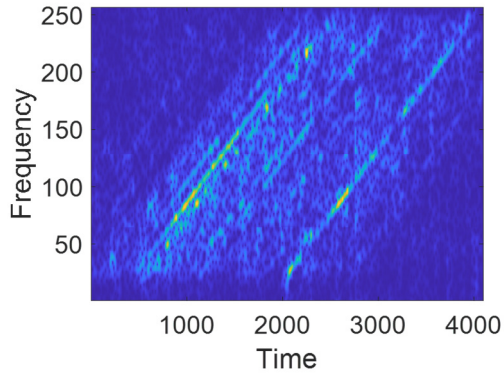
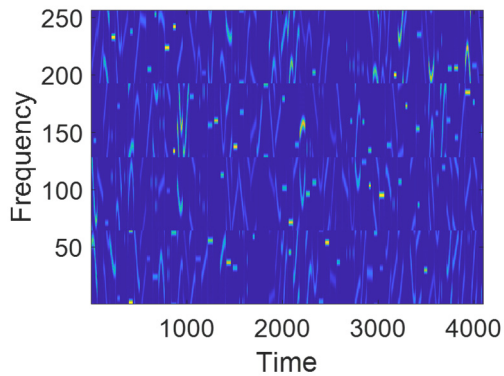


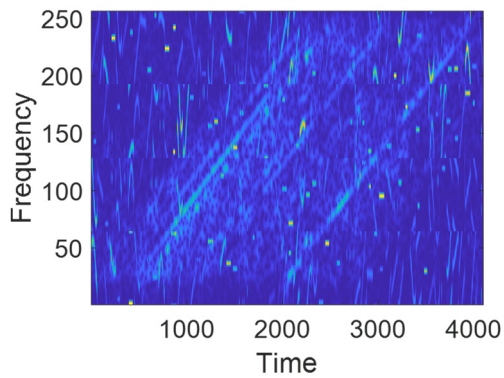
Figure 4. The variation of loss fuction with iteration steps in the training phase.



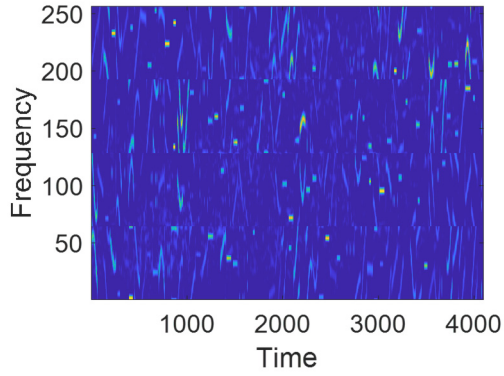
(a)



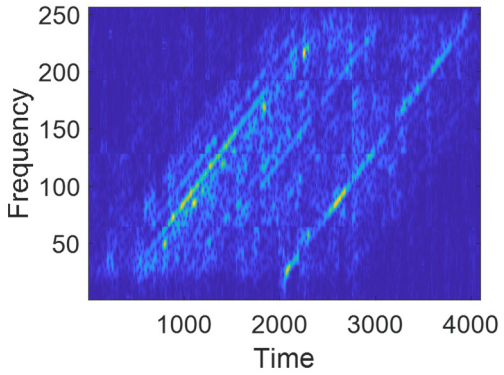
(b)



(c)



(d)



(e)

Figure 5. Comparison results after applying proposed Convolutional RPCA. (a) Original RFI-free spectrogram, (b) Simulated RFI, (c) RFI-contaminated spectrograms. (d) Extracted interference patterns. (e) Estimated target response.

Figure 5 compares the results after applying the convolution RPCA using the trained network. It is shown that the RFI signatures are clearly estimated and extracted from the data, and good reconstruction results is obtained.

5 Conclusions

In this paper, we proposed a novel RFI mitigation approach by utilizing the joint low-rank and sparse property of the RFI-contaminated radar echoes. The solution to original RPCA is unsupervised iterative optimization, in which the regularization parameters should be set as a priori and the convergence rate is generally not efficient. Alternatively, it is transformed to a supervised learning problem by a structured deep convolutional network with fixed layers, i.e., the convolutional RPCA. The proposed method can perform automatic tuning of hyperparameters and obtain excellent estimated performance for RFI suppression.

6 Acknowledgements

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7 References

[1] P. de Matthaeis, R. Oliva, Y. Soldo, "Spectrum management and its importance for microwave remote sensing," *IEEE Geosci. Remote Sens. Mag.* 2018, 6, 17-25.

[2] National Academies of Sciences Engineering and Medicine, "A Strategy for Active Remote Sensing Amid Increased Demand for Radio Spectrum," *National Academies Press*, 2015.

[3] M. Tao, J. Su, Y. Huang, L. Wang, "Mitigation of Radio Frequency Interference in Synthetic Aperture Radar Data: Current Status and Future Trends," *Remote Sens.*, 2019, 11, 2438.

[4] Y. Huang, L. Zhang, J. Li, Z. Chen, and X. Yang, "Reweighted Tensor Factorization Method for SAR Narrowband and Wideband Interference Mitigation Using Smoothing Multiview Tensor Model," *IEEE Trans. Geosci. Remote Sens.*, vol. 58, no. 5, pp. 3298-3313, 2020.

[5] J. Su, H. Tao, M. Tao, L. Wang, and J. Xie, "Narrow-Band Interference Suppression via RPCA-Based Signal Separation in Time-frequency Domain," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 10, no. 11, 2017.

[6] S. Joy, L. H. Nguyen, and T. D. Tran, "Joint Down-Range and Cross-Range RFI Suppression in Ultra-Wideband SAR," *IEEE Trans. Geosci. Remote Sens.*, vol. 99, no. 99, pp. 1–14, 2020.

[7] H. Yang, C. Chen, S. Chen, F. Xi, and Z. Liu, "SAR RFI Suppression for Extended Scene Using Interferometric Data via Joint Low-Rank and Sparse Optimization," *IEEE Geosci. Remote Sens. Lett.*, pp. 1–5, 2020.

[8] S. Itschner, X. Li, "Radio Frequency Interference (RFI) Detection in Instrumentation Radar Systems: A Deep Learning Approach," *Proc. 2019 IEEE Radar Conference*, pp. 1-4. 2019.

[9] K. Gregor and Y. LeCun, "Learning fast approximations of sparse coding," in *Proc. 27th Int. Conf. Mach. Learn.*, 2010, pp. 399–406.

[10] O. Solomon, R. Cohen, Y. Zhang, Y. Yang, Q. He, J. Luo, R. Sloun, Y. C. Eldar, "Deep Unfolded Robust PCA With Application to Clutter Suppression in Ultrasound," *IEEE Trans. on Medical Imaging*, vol. 39, no. 4, pp. 1051-1063, April 2020.