FDFNet: A Fusion Network for Generating High-Resolution Fully PolSAR Images

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***Abstract*— Deep learning shows potential superiority in the image fusion field. To solve the problem of the spatial resolution degradation of polarimetric synthetic aperture radar (PolSAR) images caused by system limitation, we propose a fully PolSAR images and DualSAR images fusion network (FDFNet). We use low resolution (LR)-PolSAR super-resolution (LPSR) and modified cross attention mechanism (MCroAM) to perform data fusion on LR-PolSAR and high resolution (HR)-dual-polarization synthetic aperture radar (DualSAR) and design a polarimetric decomposition attention module to introduce the polarimetric parameters of LR-PolSAR images to maintain polarimetric information. Besides, we use the differential information between LR-PolSAR and HR-DualSAR to guide spatial resolution reconstruction. The loss function based on the L_1 norm is used to constrain the network training process. The experimental results show the superiority of the proposed method over the existing methods in visual and quantitative evaluation. In addition, polarimetric decomposition experiments verify the effectiveness of the proposed method to maintain polarimetric information.**

***Index Terms*— Differential information, dual-polarization synthetic aperture radar (DualSAR), fully-polarimetric synthetic aperture radar (PolSAR), fusion, polarimetric decomposition.**

I. Introduction

THE fully polarimetric synthetic aperture radar (PolSAR) images can provide richer polarization information than single-polarization synthetic aperture radar (SinSAR) or dual-polarization synthetic aperture radar (DualSAR) images. Therefore, it is widely used in many fields, such as crop monitoring [1] and disaster detection [2]. However, due to the limitations of the PolSAR imaging system, it is inevitable to reduce the resolution of the fully PolSAR image to obtain rich polarimetric information. The reduction of spatial resolution will limit its practical application. To solve this problem, some scholars have proposed to use single image super-resolution reconstruction methods to enhance its resolution. Zhang *et al.* [3] proposed the super-resolution method based on polarimetric spatial correlation (SRPSC), which uses the spatial correlation between the central pixel and the neighboring pixels to reconstruct the resolution. Shen *et al.* [4] proposed a PolSAR images super-resolution reconstruction (PSSR) method based on deep learning. Some scholars use image fusion technology to improve the resolution of low resolution (LR)-PolSAR images. Lin *et al.* [5] proposed the LR-PolSAR and high resolution (HR)-SinSAR fusion network (PSFN) to obtain HR-PolSAR images. This method does not further use the HR spatial information of DualSAR, and the use of polarimetric information is relatively insufficient. Therefore, we proposed the HR-DualSAR and LR-PolSAR fusion network, which increases the utilization of HR spatial information and enhances the polarimetric information retention capability. Under this fusion framework, the polarimetric decomposition results of LR-PolSAR images are used to weight the feature maps of DualSAR images. Besides, the differential information between HR-DualSAR images and LR-PolSAR images is used to guide spatial resolution reconstruction and reduce reconstruction errors.

The remainder of this letter is organized as follows. The proposed fusion network is described in Section II. The experimental results are provided in Section III, followed by conclusions and future work in Section IV.

Manuscript received October 10, 2021; revised November 7, 2021; accepted November 10, 2021. Date of publication November 12, 2021; date of current version January 7, 2022. This work was supported by the National Natural Science Foundation of China under Grant 61671334 and Grant 62071341. *(Corresponding author: Jie Li.)*

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Digital Object Identifier 10.1109/LGRS.2021.3127958

II. Proposed Methodology

A. Fusion Framework

The PolSAR images are usually used in the form of the covariance matrix, as shown in the following equation:

$$C_3 = \begin{bmatrix} \langle |S_{\mathrm{HH}}|^2 \rangle & \sqrt{2}\langle S_{\mathrm{HH}} S_{\mathrm{HV}}^* \rangle & \langle S_{\mathrm{HH}} S_{\mathrm{VV}}^* \rangle \\ \sqrt{2}\langle S_{\mathrm{HV}} S_{\mathrm{HH}}^* \rangle & 2\langle |S_{\mathrm{HV}}|^2 \rangle & \sqrt{2}\langle S_{\mathrm{HV}} S_{\mathrm{VV}}^* \rangle \\ \langle S_{\mathrm{VV}} S_{\mathrm{HH}}^* \rangle & \sqrt{2}\langle S_{\mathrm{VV}} S_{\mathrm{HV}}^* \rangle & \langle |S_{\mathrm{VV}}|^2 \rangle \end{bmatrix} \tag{1}$$

where S_{HH} and S_{VV} represent the power of the copolarized channel, S_{HV} represents the power of the cross-polarized channel, $\langle . \rangle$ represents the statistical average operator, and * represents the complex conjugate operation.

To solve the resolution reduction of HR-PolSAR images C_x under the degradation process $C_y = f_d(C_x)$, we perform image fusion on LR-PolSAR images C_y and HR-DualSAR intensity images I_x. In the degradation process, $f_d(.)$ represents the downsampling function. As shown in Fig. 1, we jointly input the LR-PolSAR images, the HR-DualSAR images, and the polarimetric decomposition results of the LR-PolSAR images into the network to obtain HR-PolSAR images. In the network, the LR-PolSAR super-resolution

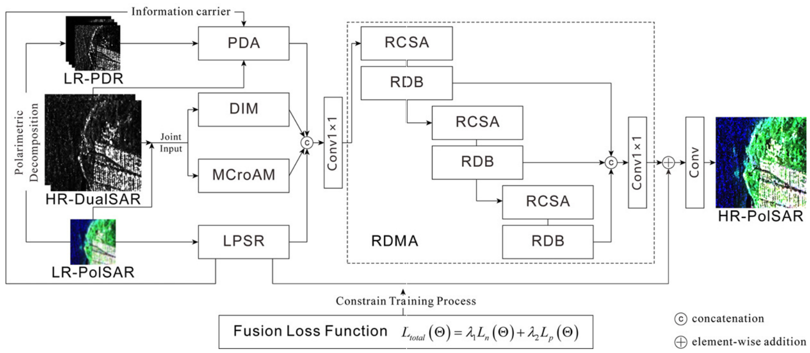

Fig. 1. Proposed fusion framework.

(LPSR) module [5] is used to perform super-resolution reconstruction processing on LR-PolSAR images. The modified cross attention mechanism (MCroAM) [5] is used to cross-weight the PolSAR data and the DualSAR data, and to enhance the information extraction capabilities for the two types of data. In MCroAM, we only modify the channels number of input data to adapt to DualSAR images. The polarimetric decomposition attention (PDA) is proposed to extract and use polarimetric decomposition information to weight synthetic aperture radar (SAR) images. The difference information module (DIM) is designed to make full use of the differential information between HR-DualSAR images and LR-PolSAR images. In the fusion network, we use the residual densely connected module with a built-in attention mechanism (RDMA) to extract information from the feature layers obtained by LPSR, MCroAM, PDA, and DIM modules. In addition, a loss function based on the L_1 norm is used to constrain the network training. Details of the proposed modules are provided in the following.

B. RDMA Module

The dense connection block [6] is proposed to improve the information flow connection problem between layers. This module can introduce the information flow of any layer into the subsequent layers and realize the information flow connection of the characteristic layers under different levels. The attention mechanism is widely used in image reconstruction tasks to recalibrate the feature layers. In this letter, we have embedded residual spatial attention and channel attention mechanisms between two densely connected blocks to effectively extract the information while recalibrating the feature maps. As shown in Fig. 1, RDMA includes a three-level structure, and each level includes residual channel attention and spatial attention joint block (RCSA), and a residual dense connection block (RDB) [6] through cascading operation to integrate different levels of feature maps. As shown in Fig. 2, RCSA includes a channel attention block and a spatial attention block. The feature maps recalibrated by the two blocks are aggregated in the form of element addition and are connected to the input feature maps of the RCSA in the form of a residual structure.

C. PDA Module

The polarimetric decomposition theory is proposed to use the polarimetric scattering matrix to reveal the physical mechanism of the scatterers, promote the full use of polarization information, and better interpret polarization data. In this letter, we use the LR polarimetric decomposition results (LR-PDR)

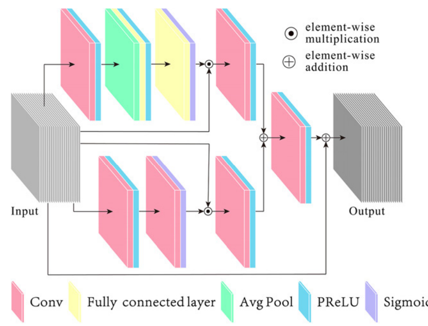

Fig. 2. RCSA block.

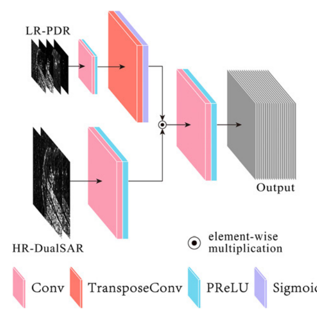

Fig. 3. PDA module.

of LR-PolSAR images, including odd scattering component, double-scattering component, volume scattering component, and helix scattering component, which were obtained by the Yamaguchi decomposition [7] to weigh the feature maps of HR-DualSAR images and enhance the polarimetric information of HR-DualSAR images.

As shown in Fig. 3, in the PDA, we first use the transposed convolutional layer to perform resolution enhancement and features extraction on the LR-PDR and use the sigmoid function to normalize the extracted feature maps. Then, we use the normalized feature maps to weight features maps of HR-DualSAR images and obtain the HR-DualSAR feature maps that are weighted by the LR-PDR.

D. DIM Module

In the fusion framework, the introduction of HR-DualSAR images can effectively enhance the spatial resolution of the corresponding polarization channel, while the spatial resolution improvement of Non-HR-DualSAR polarization channel[1] is relatively insufficient. Therefore, we use the DIM to

[1]The Non-HR-DualSAR polarization channel represents the polarization channel not included in the HR-DualSAR image.

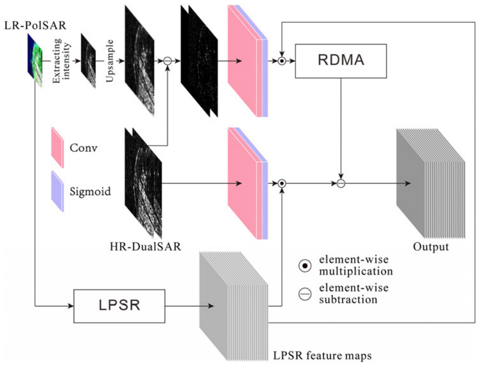

Fig. 4. Differential information module.

generate HR features of the Non-HR-DualSAR polarization channel for LR-PolSAR images' enhancement in the subsequent process.

The structure of the DIM is shown in Fig. 4. To illustrate the differential information module intuitively, we take the fusion of HR-DualSAR (HV, VV) images and LR-PolSAR data as an example to describe the module in detail. In this module, we interpolate the LR-PolSAR images and extract the polarization channel intensity images (HH) without corresponding HR images guidance. Then, we use HR-DualSAR intensity images to subtract them to obtain the initial differential information results ($D_{\mathrm{LR}}^{\mathrm{HV\text{-}HH}}, D_{\mathrm{LR}}^{\mathrm{VV\text{-}HH}}$). In the next steps, we perform element multiplication operations on initial differential information results and LR-PolSAR feature maps to obtain differential information weighted feature maps ($F_{\mathrm{LR}}^{\mathrm{HV\text{-}HH}}, F_{\mathrm{LR}}^{\mathrm{VV\text{-}HH}}$). Through the RDMA module for features extraction and features aggregation, the HR differential information weighted feature maps ($F_{\mathrm{HR}}^{\mathrm{HV\text{-}HH}}, F_{\mathrm{HR}}^{\mathrm{VV\text{-}HH}}$) are obtained. Finally, the HR-DualSAR weighted feature maps ($F_{\mathrm{HR}}^{\mathrm{HV}}, F_{\mathrm{HR}}^{\mathrm{VV}}$) and the HR differential information weighted LR-PolSAR feature maps ($F_{\mathrm{HR}}^{\mathrm{HV\text{-}HH}}, F_{\mathrm{HR}}^{\mathrm{VV\text{-}HH}}$) are subjected to element subtraction to obtain HR polarization channel images (HH) and weighted LR-PolSAR feature maps ($F_{\mathrm{HR}}^{\mathrm{HH}}, F_{\mathrm{HR}}^{\mathrm{HH}}$), which is directly used in the subsequent images fusion.

E. Fusion Loss Functions

The PolSAR images have the characteristics of a large numerical dynamic range and complex data distribution. Compared with the L_2 norm, which is sensitive to outliers, the L_1 norm is more suitable for data with high dynamic range and complex data distribution characteristics. Therefore, the loss function in this letter adopts the form of the L_1 norm, which includes two parts: a numerical loss function and a dual-polarization information loss function. The numerical loss function is used to maintain the consistency of image numerical information, and the dual-polarization information loss function is used to maintain the consistency of image polarization information. The fusion loss function can be defined as follows:

$$L_{\mathrm{total}}(\Theta) = \lambda_1 L_n(\Theta) + \lambda_2 L_p(\Theta) \tag{2}$$

where $L_{\mathrm{total}}(\Theta)$ represents the total loss function, $L_n(\Theta)$ represents the numerical loss function, and $L_p(\Theta)$ represents the polarimetric information loss function. λ_1 and λ_2 are regularization parameters, and they are adaptively determined

TABLE I

TRAIN DATASETS' INFORMATION

Region	Res	Size	Data
San Francisco	8m	6400×2400×9	HR-PolSAR
	16m	3200×1200×9	LR-PolSAR
	8m	6400×2400×2	HR-DualSAR (HV, VV)
San Francisco	8m	5200×2400×9	HR-PolSAR
	16m	2600×1200×9	LR-PolSAR
	8m	5200×2400×2	HR-DualSAR (HV, VV)

TABLE II

TEST DATASETS' INFORMATION

Region	Res	Size	Data
San Francisco	16m	1200×1200×9	LR PolSAR
	8m	2400×2400×2	HR DualSAR (HV, VV)
Quebec	16m	2048×1708×9	LR PolSAR
	8m	1024×854×2	HR DualSAR (HV, VV)

by the values of $L_n(\Theta)$ and $L_p(\Theta)$

$$L_n(\Theta) = \frac{1}{N}\sum_{i=1}^{N}\left\|\Re^i - f_n\left(C_y^i, I_x^i\right)\right\|_1 \tag{3}$$

$$L_p(\Theta) = \frac{1}{N}\sum_{i=1}^{N}\left\|\left(I_{x,j}^i - \Im_j\left(C_u^i\right)\right) - \Im_j\left(f_n\left(C_y^i, I_x^i\right)\right)\right\|_1 \tag{4}$$

$$\lambda_1 = \frac{L_n(\Theta)}{L_n(\Theta) + L_p(\Theta)}, \quad \lambda_2 = \frac{L_p(\Theta)}{L_n(\Theta) + L_p(\Theta)} \tag{5}$$

where $\Re^i$ is the residual between the LR-PolSAR images' upsampling results C_u^i, the reference HR-PolSAR images C_x^i and C_y^i represent the observed LR-PolSAR images, and I_x^i represents the HR-DualSAR intensity images. $f_n(.)$ represents the input of the proposed fusion network. N represents the number of training image pairs. $\Im(.)$ represents the intensity image extraction operator. The subscript j represents two of the polarization channels, HH, HV, and VV, which are determined by the polarization channel of the input DualSAR. In practical applications, we extract different polarization intensity images to calculate the loss function according to the polarization channel of the DualSAR images used.

III. EXPERIMENT AND ANALYSIS

To verify the effectiveness and robustness of the proposed fusion method, we conduct simulation experiments, real experiments, and polarization information analysis experiments. We use RADARSAT-2 data as experimental data, which is C-band data. The details of the train data and test data used in the experiment are listed in Tables I and II. Since there is no DualSAR and PolSAR image fusion method, in simulation experiments and real experiments, we compare with the current mainstream four PolSAR image-enhancement methods, including interpolation method (Bicubic), super-resolution reconstruction methods (SRPSC [3] and PSSR [4]), SinSAR, and PolSAR image fusion method (PSFN [5]). To ensure the fairness of the comparison experiment, DualSAR input is used to replace SinSAR input in the PSFN. In the quantitative evaluation, we select two quantitative evaluation indicators, peak signal-to-noise ratio (PSNR), and mean absolute error (MAE) to measure the fidelity of PolSAR images' information and the error of the reconstructed images, respectively. According to the quantitative evaluation system in PSFN [5], we quantitatively calculate three components of the Pauli decomposition, including the odd scattering component P_1,

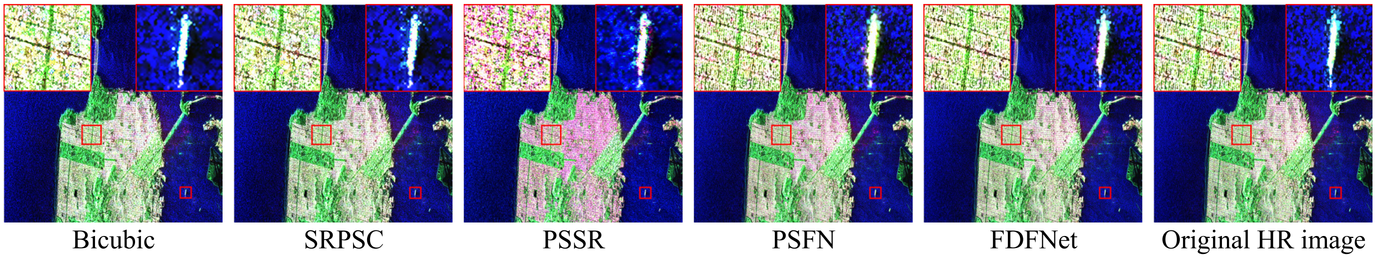

Fig. 5. Comparison results of simulation experiments.

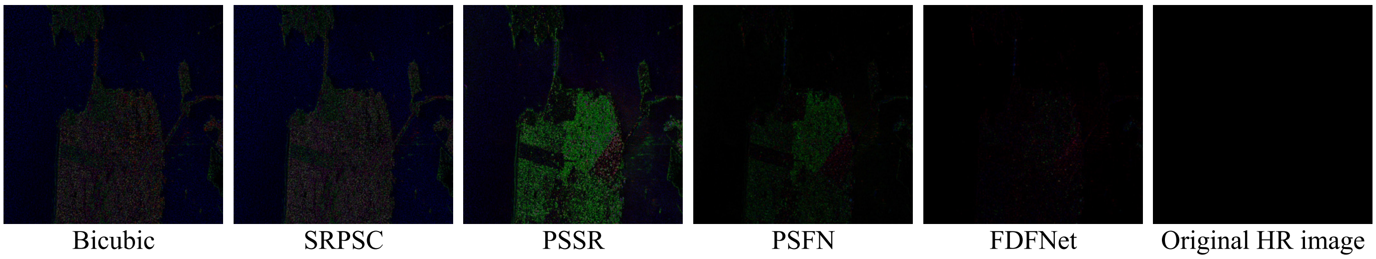

Fig. 6. Residual results of simulation experiments.

double-scattering component P_2, and volume scattering component P_3. In the visual evaluation experiment, we perform the Pauli composition on the results and calculate the residuals of the Pauli composition results. In the polarimetric analysis experiments, we perform polarimetric decomposition on the fusion results and compare the results with the corresponding HR-PolSAR images. The code link of the proposed method is (https://github.com/LiupengLin/FDFNet).

A. Simulation Experiments

In the simulation experiments, we downsample the HR-PolSAR images to get the LR-PolSAR images and extract the intensity of it to get the HR-DualSAR images. The LR-PolSAR images and HR-DualSAR images are used as test data, and the HR-PolSAR images are used as reference data for quantitative evaluation. The data used in the experiment have been preprocessed by sigma radiometric calibration, nonlocal means despeckle processing, and multilook processing.

As shown in Fig. 5, in the enlarged image on the left in densely built-up areas, compared with the super-resolution methods, the proposed method can effectively reconstruct the texture details of the ground features. At the same time, compared with PSFN, the proposed fusion method has fewer artifacts. In the enlarged image on the right, the strong scatterer reconstructed by the proposed method has good color fidelity while reconstructing detailed information, and no obvious defocusing phenomenon occurs. Besides, as shown in Fig. 6, in the residual results of the original HR-PolSAR images, the proposed method has lower residuals, and all comparison methods have more obvious residual information. As shown in Table III, the proposed method is significantly superior to other comparison methods in quantitative indicators.

B. Real Experiments

In the real experiment, the LR-PolSAR images and the HR-DualSAR images used were acquired in the standard mode and fine mode of the RADARSAT-2 satellite, respectively. The HR-PolSAR fusion results are obtained by fusing the LR-PolSAR images in the standard mode and the HR-DualSAR images in the fine mode. The HR-PolSAR images acquired in fine mode are used as reference data for quantitative evaluation. The real experimental data are also preprocessed in the same way as the simulated data. In addition, image registration processing has been carried out on the data in the two modes.

In the real experiment, we select two types of land coverage for visual evaluation, including densely built-up and vegetation. As shown in Fig. 7, the enlarged image on the left is a densely built-up area, and the one on the right is a vegetation area. In densely built-up areas, both fusion methods can effectively reconstruct detailed information, while the results of super-resolution methods are relatively smooth. Compared with PSFN, the detailed information of the proposed method is closer to the HR-PolSAR images in the fine mode. In vegetation areas, the results of the proposed method have clearer edges and better color fidelity. At the same time, as shown in Fig. 8, in the residual image, the residual of the

TABLE III

QUANTITATIVE EVALUATION RESULTS OF RS-2 (SAN FRANCISCO)

Method	Bicubic	SRPSC	PSSR	PSFN	FDFNet
PSNR ($\|P_1\|^2$)	45.63	46.04	47.25	52.64	**52.77**
PSNR ($\|P_2\|^2$)	43.16	42.84	43.42	**49.97**	49.48
PSNR ($\|P_3\|^2$)	51.39	50.89	52.53	65.37	**81.47**
PSNR (mean)	46.73	46.59	47.73	55.99	**61.24**
MAE ($\|P_1\|^2$)	0.284	0.236	0.254	0.078	**0.069**
MAE ($\|P_2\|^2$)	0.199	0.190	0.213	0.089	**0.083**
MAE ($\|P_3\|^2$)	0.035	0.034	0.037	0.013	**0.002**
MAE (mean)	0.173	0.153	0.168	0.060	**0.051**

TABLE IV

QUANTITATIVE EVALUATION RESULTS OF RS-2 (QUEBEC)

Method	Bicubic	SRPSC	PSSR	PSFN	FDFNet
PSNR ($\|P_1\|^2$)	50.77	50.74	51.72	56.47	**56.94**
PSNR ($\|P_2\|^2$)	49.95	50.21	50.76	58.50	**58.63**
PSNR ($\|P_3\|^2$)	50.35	50.60	54.17	71.41	**80.79**
PSNR (mean)	50.36	50.52	52.22	62.13	**65.45**
MAE ($\|P_1\|^2$)	0.095	0.083	0.099	**0.030**	0.031
MAE ($\|P_2\|^2$)	0.103	0.086	0.106	**0.023**	0.026
MAE ($\|P_3\|^2$)	0.152	0.129	0.084	0.009	**0.002**
MAE (mean)	0.117	0.099	0.096	0.021	**0.020**

Fig. 7. Comparison results of real experiments.

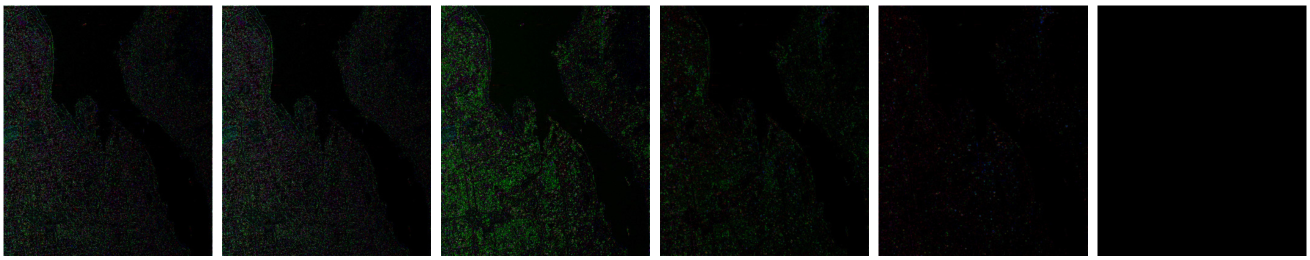

Fig. 8. Residual results of real experiments.

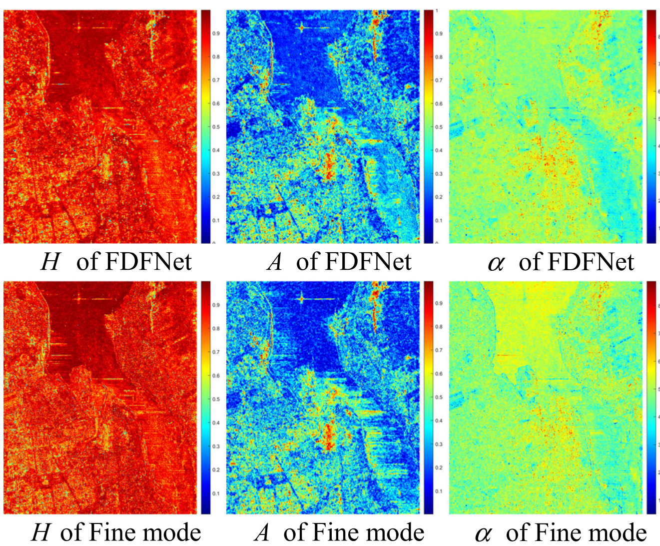

Fig. 9. Polarimetric decomposition results.

proposed method is lower. Quantitative evaluation indicators show that the proposed method has better details and lower reconstruction errors, as shown in Table IV.

C. Polarization Decomposition Experiment

To verify the ability of the fusion network to maintain polarimetric information, we use $H/A/\alpha$ polarimetric decomposition [8] to analyze the scattering characteristics of the result. To prove the practical application capability of the fusion network, polarimetric analysis experiments are all based on the fusion results of real experiments.

As shown in Fig. 9, in the polarimetric decomposition results, including the polarimetric entropy (H), anisotropy (A), and average alpha angle (α), the decomposition results of the proposed method are close to that of the HR-PolSAR images in the fine mode. It shows that the proposed method can better maintain the polarimetric information and can effectively extract the polarimetric parameters.

IV. Conclusion

In this letter, a fusion network of LR fully PolSAR images and HR DualSAR images is proposed. By introducing polarimetric decomposition information and differential information, the two kinds of data are effectively fused. In addition, the L_1 norm loss function makes the trained model more suitable for PolSAR images. Compared with the existing PolSAR images resolution enhancement methods, the proposed method can effectively reconstruct the texture details while maintaining the inherent polarimetric information of the PolSAR images. The proposed network is a data-driven method, and the accuracy of the model depends on the training dataset. Therefore, the development of a weakly supervised fusion method that combines physical mechanisms is one of the future trends.

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