An Image Fusion Method of SAR and Optical Images, Based on Image Intensity Fields, by Reducing the Effect of Speckle Noise

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Abstract: This study proposes an improved fusion method, that takes advantage of the combined strengths of existing fusion methods. First, current methods are compared using a fusion of noisy images from the Synthetic Aperture Radar (SAR) database, with optical images acquired at the same location and time. The obtained image and metric results showed that combining optical images with de-noised SAR provides better performance. Experiments have also shown that removing noise in SAR data causes the loss of important data in images. The proposed method divides the image into small patches in the noise removal phase. By calculating the standard deviation of these sub-patches, a different noise reduction ratio is applied for each region, thus preventing the loss of important detail features in the image. The proposed method has been compared with fusion methods recognized in the existing literature. Experimental results demonstrate that the proposed method, performs better than current fusion methods. The proposed method also yields better metric results, over other methods and it also eliminates the noise problems, often present in the images.

Keywords: image fusion; synthetic aperture radar; optical image; noise reduction

1 Introduction

Image fusion combines images with different properties, such as SAR, optical, and hyperspectral, to obtain images with more information. Optical images are rich in spatial information. On the other hand, SAR images are good for representing cloudy, foggy, and dark areas and reflecting the properties of different materials. SAR-optical image fusion is an area that has been explored in recent years because it contains complementary information about the scene being viewed. In classical image fusion, the fusion of images acquired by a single method or sensor provides acceptable results. However, there are still processes that need to be developed, including different imaging methods in SAR-optical image fusion [1] [2]. Image fusion is an important research area to improve the understandability and usability of remote sensing data [3].

The fusion of data containing different image methods can be performed for object recognition, image enhancement, and object classification. As shown in Figure 1, these processes include the tasks of data matching, data/object relationships, attribute/identity estimation, and data fusion results. In remote sensing image fusion, these four steps can be divided into two groups. Data matching creates the data/object relationship pair in the aligned and associated field, while attribute/identity prediction and data fusion result fields form the data fusion phase. As a result of aligned and associated data field measurements, related objects are connected to each other. The data fusion phase, on the other hand, compares data obtained by mathematical or machine learning methods using aligned and correlated data [4].

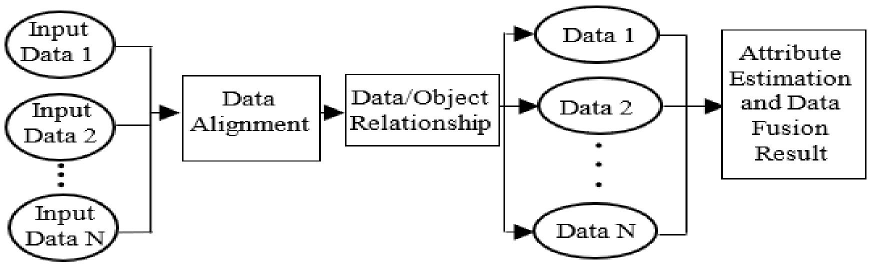


Figure 1
Flow Chart of the general data fusion process

As a result of developments in the acquisition of SAR data, improving the quality of SAR images, obtaining meaningful information from SAR images, and using the obtained data have become important subject [5]. Coherent imaging of SAR systems generates multiplicative speckle noise, which significantly affects the interpretability of SAR images. A new SAR speckle noise removal method was proposed based on weighted nuclear norm minimization (WNNM) [6]. Speckle noise degrades the result of various operations, such as segmentation and edge detection, used during the fusion process. For this reason, speckle noise reduction is crucial in eliminating noise, especially in homogeneous regions, while ensuring accurate edge detection [7]. In addition, new methodologies, including the use of a specially designed total fractional-order variation model for multiplicative noise removal and contrast enhancement, make further improvements in the pre-processing of SAR images for fusion [8]. This approach not only reduces noise but also increases contrast, optimizing the quality for subsequent analysis. In addition, combined advanced filtering with supervised classification strategically reduces speckle noise while preserving key image features, integrating advanced algorithms with machine learning to preserve key details [9]. Another technique uses a DFT-based framework that adapts noise reduction to the specific characteristics of every SAR image, delivering precise speckle reduction with respect to different frequencies and specific regions in the images [10]. Combined advanced noise reduction methods enhance the stage of SAR image pre-processing, generating more accurate and informative results for image fusion.

Several methods for aligning homogeneous image regions are needed to fuse SAR and optical images. However, these methods are not suitable for SAR- optical image alignment because there are significant geometric and radiometric differences between the two methods. To eliminate this problem, the SEN1-2 dataset has been published [11]. This dataset is the first open dataset to contain SAR-optical data pairs from the same scene and time.

Automatic matching of SAR and optical images is an important task in many remote sensing applications. However, traditional matching methods provide limited performance due to different imaging modalities. Based on the observation that structural features are preserved in different modality images, a new feature-based method is proposed to handle SAR and optical image matching effectively [12]. Due to the nonlinear radiometric and geometric relationship, the optical and SAR image-matching task still needs to be solved. To solve this problem, it is proposed to use a CNN architecture that learns deep and dense features on a pixel basis [13]. A joint sparse display method (JSR) was proposed to remove the noise in the source images used in fusion methods from the scene and obtain a noise-free fused image [14]. The need to process large image data poses challenges in change detection due to noise in SAR images. To improve the change detection accuracy and reduce the processing time, a new unsupervised change detection algorithm for SAR images is proposed [15]. In order to investigate the effect of noise problem in source images on image fusion, it has been shown that fusion processes with noise removal images provide better performance than metric results [16].

In fusion studies, noise removal is applied with different methods as a pre-processing step. In the studies examined, it was seen that the noise reduction process was applied to the whole scene. When the structure of the scenes is examined, it has been determined that not all of the scenes used contain information of equal intensity. Studies have shown that applying the same noise reduction ratio to any part of the scene that does not contain information with the same intensity reduces the success of the fusion result. During the noise reduction process, it has been determined that applying a low-intensity noise reduction ratio to the areas with intense information in the scene prevents the loss of important data. Likewise, it has been observed that high-intensity noise removal applied to low-intensity areas results in the complete removal of noise, improving the fusion process result. This study aims to combine the capability of fusion methods with the success of noise removal. By combining these two methods adaptively, besides the visual success of the images obtained by combining the SAR-optical data, the metric results increased by 5%. Similarly, while noise reduction methods are applied to SAR images, the images are divided into 32x32 pixels small-size frames. The image intensity of these frames was determined, and noise reduction was applied according to the intensity values obtained. This method avoids significant data loss caused by fixed noise reduction applied to the entire image. As a result of the experiments, a higher fusion rate was achieved, with a 10% improvement in the metric results.

2 Proposed Method

It is well known that removing noise in SAR data positively affects the SAR-optical fusion process. However, the metric analysis showed that when noise was removed from the data, some important data were lost along with the noise. It is desired that important data is lost as little as possible and the fusion process can be more efficient. For this purpose, the effect of detecting the intensity areas in the SAR data and applying different noise removal rates to these areas on the fusion process has been examined.

The intensity fields were created by using a 32x32 pixels frame for the SAR data with a size of 256x256 pixels (Figure 2 (a)) and detecting sixty-four different intensity fields by advancing the frame by one step at each step (Figure 2 (b)). The noise removal rate (λ) to be applied to the intensity patches was determined using seven different criteria after the intensity average (1) and standard deviation (2) of the pixels in the 32x32 pixels frame (Figure 2 (c)) are determined (Table 1).

$$\text{Average (A)} = \frac{1}{n}\sum_{i-1}^{n} X_i \tag{1}$$

$$\text{Standard Deviation (S)} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - A)^2} \tag{2}$$

The n used in the equations refers to the number of pixels in the 32x32 pixels frame. X represents the value between 0-255 of each pixel in a 32x32 pixels frame.

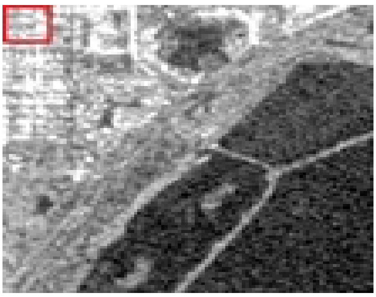
Here, λ stands for the noise reduction value of the noise removal algorithm. The larger the obtained standard deviation value, the greater the difference in pixel density in the frame. This means that the area between frames needs to contain more information. The smaller the value obtained, the more similar the area in the frame and the lower the information density.

Table 1

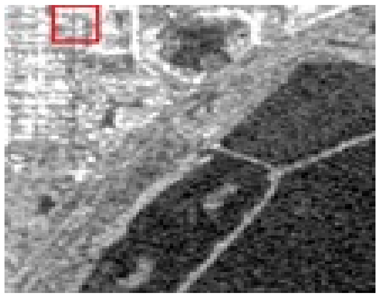
λ Values Corresponding to Standard Deviation Value

Standard Deviation Value	λ Value
<10	35
<15	30
<20	25
<25	20
<35	15
<45	10
>=45	5

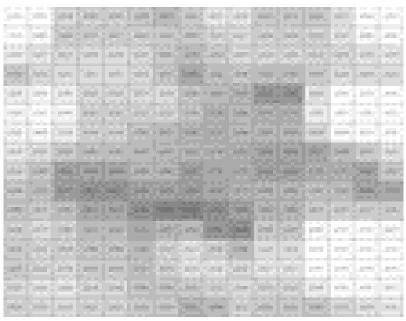
Experiments have shown that it is beneficial to apply a low noise reduction ratio to areas with intense information and a high noise reduction ratio to areas where the information is not intense. The results obtained provided a more successful fusion by approximately 10% compared to the standard applied noise removal process.



(a) 32x32 Pixel Frame



(b) 32x32 Pixel Unit Advancement of Frame



(c) 32x32 Pixel Unit Intensity Table

Figure 2

Detection of density areas in SAR data

As a noise reduction algorithm, the proposed method used sparsity-based speckle removal (SDD) [7]. SDD used different standards controlled by a single parameter and provided better or similar noise removal compared to state-of-the-art methods with shorter execution times. Speckle removal in SAR images using the SDD algorithm was performed according to the following formulation:

$$J(F) = \sum_{P} (F_P - G_P)^2 + \lambda \wedge (|(\partial F)_P|, f) \tag{3}$$

where, G represents the speckled image, F shows the denoised image, P represents the pixel index number in the image, λ is the noise reduction ratio, and f is the norm value to be applied in the arrangement. When f is 0, to obtain the l0 - norm, the exponentiation operator ∧(x, f) is defined as follows:

$$\wedge (x, f) = \begin{cases} 0 & x = 0, \quad f = 0 \\ x^f & \text{otherwise} \end{cases} \tag{4}$$

In the cost function, the first term is a suitability term that makes F similar to G. The second term is TV editing, which implies a penalty for changes in the image gradients. In this formulation, the l0- norm is when f is 0, the l1 - norm is when f is 1, and the fractional norm is obtained when f is between 0 and 1.

The proposed method has considered the intensity fields in the SAR images and increases the performance of the fusion results by preventing the fusion process from being affected by noise. The operations in (1) and (2) has determined the intensity fields. The value of the standard deviation resulting from these equations and the value of the λ-variable used as the noise reduction value in the noise removal algorithm have been updated depending on a set of criteria. These criteria were determined to be optimal through sensitivity analysis. These parameters were found to cause changes in memory usage and execution time, thus not affecting the important data in the image. The λ-parameters, which vary in a range of [5-35], were changed iteratively to achieve maximum noise removal and minimum data loss. The algorithm involving intensity range detection and determination of the noise reduction ratio to be applied:

Algorithm: Intensity Area Detection

Input: Image G, parameters λ, f, and ∈d, maxiteration ← 5, dimension←256
Initialization: $\tilde{f} \leftarrow (2 - f)$, $\epsilon \leftarrow \epsilon_d \lambda^{-\tilde{f}}$, $\tilde{G} \leftarrow G/\lambda$
$v_F^{(1)} \leftarrow$ image2vector($\tilde{G}$)
for i = 1 to dimension
  l←32
  j←j+32
  for k=1 to dimension
  frame←Image G(i:j;k:l)
  S ← $frame_i$ using (2)
  end for
end for
Output: result image $F \leftarrow \tilde{F}\lambda$

In this study, SAR-optical image fusion was applied using five image fusion methods (Multi-Scale Weighted Gradient-Based (MWGF) [17], Image Fusion with Guided Filtering (GFF) [18], Multi-Sensor Image Fusion Based on Fourth Order Partial Differential Equations (FOPDE) [19], Wavelet-Based Image Fusion (DWT) [20], Multi-Focus Image Fusion with a Deep Convolutional Neural Network (CNN) [21].

Metrics are critical in deciding which algorithm or criterion to use for comparing image processing techniques and advanced image evaluation. Since image fusion is used in many geospatial and night vision applications, it is important to understand these techniques and compare the methods [22]. The five metrics used to evaluate the fusion performance are divided into four groups. Groups of evaluation metrics are shown in Table 2.

Table 2

Reference informal objective evaluation metrics

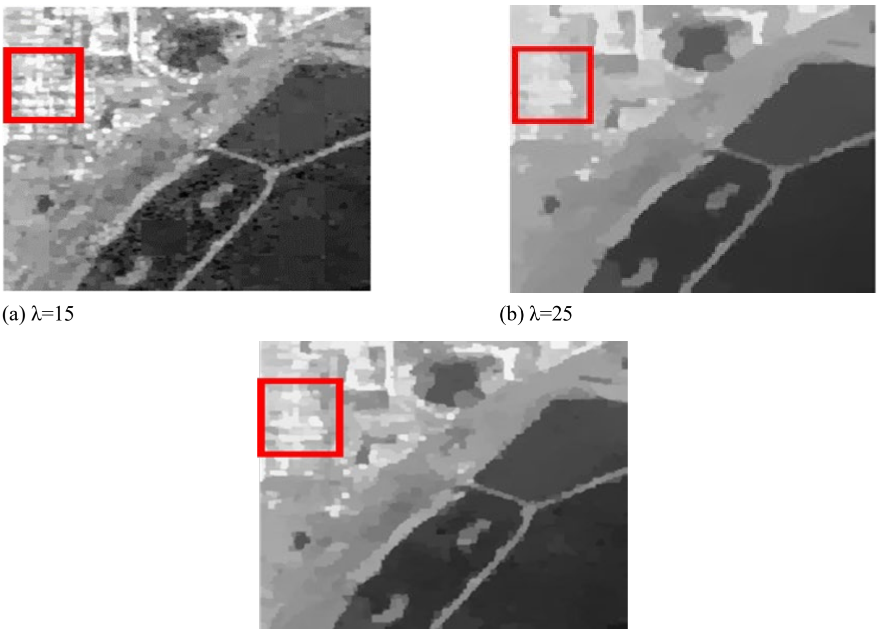
Category	**Name**	**Symbol**
Information theory-based metrics	Normalized Mutual Information	Q_{MI}
	Nonlinear Correlation Information Entropy	Q_{NCIE}
Image attribute-based metrics	Gradient-Based Fusion Performance	Q_G
Metrics based on image structural similarity	Yang's Metric	Q_Y
Metrics inspired by human perception fusion measures	Chen-Blum Metric	Q_{CB}

3 Experimental Studies

The Sentinel-1 SAR dataset and the Sentinel-2 optical dataset were used to investigate the performance of the proposed method [11]. Five different fusion algorithms recognized in the literature were applied to the images to perform the fusion process. In addition, five different metric evaluations recognized in the literature were used to evaluate the quantitative results and the qualitative success of the method.

In this study, experimental results for each algorithm are presented separately, including visual and metric results. The parameters of all algorithms were determined experimentally. The metric results for each algorithm were calculated by computing the values obtained as a result of the fusion of twenty image parts, and the average values were reported. In the experimental studies, the algorithms were performed on the Intel i5 9500T processor using the R2019b version of the Matlab software.

The noise removal step before the fusion process was applied to the SAR data with different λ-values using the SDD algorithm. Results were obtained using different noise removal rates on a sample image to visually detect important data lost during the applied noise removal process, as shown in Figure 3. Examples of important areas thought to be lost during noise removal are shown in red square. The intense areas visible in the original image were lost during noise removal and took the form of a low-intensity area. This situation caused the desired contribution of SAR data to decrease during the fusion process and affected the success of the fusion process. In order to prevent the loss of important data during noise removal, different noise removal rates were applied to different intensity areas in the study. The results are seen in Figure 3 (c).



(a) λ=15 (b) λ=25

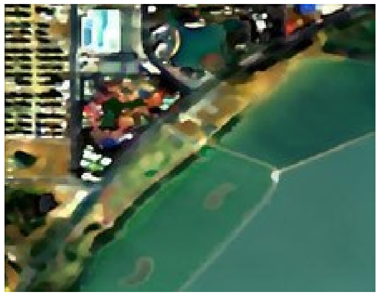
(c) Recommended Method λ=5-35

Figure 3

Comparison of SAR data with different λ-values applied

The results obtained when fixed noise reduction rates are applied to the sample image are shown in Figure 3 (a) (λ=15) and Figure 3 (b) (λ=25). Considering the intensity difference with the proposed method, the image obtained as the noise removal result is shown in Figure 3 (c). Examples of the fusion results obtained with the denoised images are shown in Figure 4, and the data obtained by comparing the results with the metrics are shown in Table 3.

(a) λ=15



(b) λ=25

(c) Recommended Method λ=5-35

Figure 1
Examples of the fusion results obtained with the denoised images

Examining the fusion results, it is clear that speckle noise in the SAR data cannot be eliminated if the λ-value is kept low, and some important data is lost if the λ-value is kept high. In the experiments performed with the proposed method, it was found that the speckle noise was removed at an acceptable level, and the loss of important features was very small. Experimental studies were conducted on many images from the dataset to test the success of the proposed method on data with different scenes. In order to compare the success of the fusion algorithms with the performed studies, the results of the determined fusion algorithms were compared with the metrics, and the obtained results are shown in Table III. When the table is examined, the metric values obtained from four noise removal processes can be seen. The results of the fusion processes performed without noise removal were originally stated, and the lowest metric results were obtained for almost all fusion algorithms. These studies showed that the results of fusion processes with noisy SAR data were corrupted by noise.

When the results of the SAR data with a λ-value of 15 and the SAR data with a λ-value of 25 are examined, it can be seen that reducing the amount of noise has a positive effect on the results. However, as the λ-value increases, the loss of important information in the SAR data increases, and the metric results deteriorate.

Table 3
Metric results of fusion algorithms

Fusion Algorithms		Metric Algorithms					Execution Time
		Q_{MI}	Q_{NICE}	Q_G	Q_Y	Q_{CB}	
MWGF	(a)	0.904	0.861	0.655	0.994	0.741	3.654
	(b)	0.910	0.873	0.680	0.996	0.764	3.663
	(c)	0.921	0.898	0.708	0.997	0.791	3.654
	(d)	**0.981**	**0.915**	**0.738**	**0.999**	**0.810**	**3.607**
GFF	(a)	0.542	0.828	0.624	0.956	0.651	2.512
	(b)	0.684	0.834	0.763	0.961	**0.751**	2.544
	(c)	0.781	0.854	0.784	0.974	0.732	2.479
	(d)	**0.891**	**0.907**	**0.884**	**0.988**	0.748	**2.477**
FOBDE	(a)	0.452	0.813	0.502	0.851	0.510	0.225
	(b)	0.684	0.882	0.691	0.886	0.660	0.223
	(c)	0.891	0.896	0.734	0.902	0.772	0.247
	(d)	**0.998**	**0.904**	**0.890**	**0.992**	**0.814**	**0.220**
DWT	(a)	0.248	0.815	0.542	0.842	0.665	1.001
	(b)	0.465	0.878	0.682	0.877	0.783	1.226
	(c)	0.785	0.896	0.775	**0.990**	0.842	1.079
	(d)	**0.899**	**0.933**	**0.864**	0.927	**0.916**	**1.000**
CNN	(a)	0.842	0.851	0.648	0.984	0.715	4.763
	(b)	0.876	0.874	0.671	0.989	0.784	4.874
	(c)	0.918	0.896	0.695	0.993	0.805	4.730
	(d)	**0.988**	**0.924**	**0.755**	**0.999**	**0.895**	**4.654**

(a) Original Image (b) λ =15 (c) λ =25 (d) Recommended Method

The highest metric values were obtained in the experiments with variable λ ratio, which is the proposed method. When the results are examined, an average of 10% improvement is observed in metric values. It can be noted here, that the proposed method achieve results in a short time, does not need to label the data used and provides accuracy without the need for long training times.

Conclusions

In this study, an adaptive noise reduction method is proposed, to remove the noise in the data used in the fusion process and to increase the success of the fusion methods. Studies have shown that the parameters of fusion methods should be adjusted before the fusion process. The data obtained by updating the parameters are more effective than those obtained in the previous studies, but did not provide satisfactory results. This could be the result of the fact, that noise removal in the SAR data, also affected important data in the images. Considering that this problem can be solved by applying different noise removal rates, to different intensity regions in the images used, these applications were applied. The results from the study show that it can be beneficial, to use different noise reduction ratios, when combining areas with dissimilar intensities.

Optimization methods can determine the parameter values of the fusion and noise reduction algorithms, which needs to be adjusted according to the data in future studies. In this way, finding the optimal values for the parameters becomes easier and faster. Moreover, the proposed technique can be used as a successful pre-processing process, especially for deep learning methods, that have become popular in recent years. It is predicted that with good pre-processing, the classification and visualization performance will only increase, in any future deep learning approaches.

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References

[1] Merkle, N., Wenjie, L., Auer, S., Müller, R., & Urtasun, R. Exploiting Deep Matching and SAR Data for the Geo-Localization Accuracy Improvement of Optical Satellite Images. Remote Sensing, 2017, 9. https://doi.org/10.3390/rs9060586

[2] Müller, R., Krauß, T., Schneider, M., & Reinartz, P. Automated Georeferencing of Optical Satellite Data with Integrated Sensor Model Improvement. Photogrammetric Engineering & Remote Sensing, 2012, 78, 61–74. https://doi.org/10.14358/PERS.78.1.61

[3] Yılmaz, Ş. Ç., & Güngör, O. Improving SVM Classification Accuracy with Image Fusion-Based Gabor Texture Features. Turkish Journal of Remote Sensing and GIS, 2020, 1 (1), 34-44

[4] Schmitt, M., Tupin, F., & Zhu, X. X. Fusion of SAR and optical remote sensing data - Challenges and recent trends. 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2017, 5458–5461. https://doi.org/10.1109/IGARSS.2017.8128239

[5] Jia, Z., Guangchang, D., Feng, C., Xiaodan, X., Chengming, Q., & Lin, L. A Deep Learning Fusion Recognition Method Based On SAR Image Data. Procedia Computer Science, 2019, 147, 533–541. https://doi.org/https://doi.org/10.1016/j.procs.2019.01.229

[6] Bo, F., Lu, W., Wang, G., Zhou, M., Wang, Q., & Fang, J. A Blind SAR Image Despeckling Method Based on Improved Weighted Nuclear Norm Minimization. IEEE Geoscience and Remote Sensing Letters, 2022, 19, 1–5. https://doi.org/10.1109/LGRS.2022.3217033

[7] Ozcan, C., Sen, B., & Nar, F. Sparsity-Driven Despeckling for SAR Images. IEEE Geoscience and Remote Sensing Letters, 2016, 13(1), 115–119. https://doi.org/10.1109/LGRS.2015.2499445

[8] Zhou, Y., Li, Y., Guo, Z., Wu, B., & Zhang, D. Multiplicative Noise Removal and Contrast Enhancement for SAR Images Based on a Total Fractional-Order Variation Model. Fractal and Fractional, 2023, 7(4), 329. https://doi.org/10.3390/fractalfract7040329

[9] Parhad, S. V., Warhade, K. K., & Shitole, S. S. Speckle noise reduction in SAR images using improved filtering and supervised classification. Multimedia Tools and Applications, 2023, https://doi.org/10.1007/s11042-023-17648-0

[10] Jain, V., Shitole, S., & Rahman, M. Performance evaluation of DFT based speckle reduction framework for synthetic aperture radar (SAR) images at different frequencies and image regions. Remote Sensing Applications: Society and Environment, 2023, https://doi.org/10.1016/j.rsase.2023.101001

[11] Schmitt, M., Hughes, L., & Zhu, X. The SEN1-2 dataset for deep learning in SAR-optical data fusion. In ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences: 2018, Vols. IV–1. https://doi.org/10.5194/isprs-annals-IV-1-141-2018

[12] Fan, J., Ye, Y., Liu, G., Li, J., & Li, Y. Phase Congruency Order-Based Local Structural Feature for SAR and Optical Image Matching. IEEE Geoscience and Remote Sensing Letters, 2022, 19, 1–5. https://doi.org/10.1109/LGRS.2022.3171587

[13] Zhang, H., Lei, L., Ni, W., Tang, T., Wu, J., Xiang, D., & Kuang, G. Optical and SAR Image Matching Using Pixelwise Deep Dense Features. IEEE Geoscience and Remote Sensing Letters, 2022, 19, 1–5. https://doi.org/10.1109/LGRS.2020.3039473

[14] Ma, X., Hu, S., Liu, S., Wang, J., & Xu, S. Noisy Remote Sensing Image Fusion Based on JSR. IEEE Access, 2020, 8, 31069–31082. https://doi.org/10.1109/ACCESS.2020.2973435

[15] Wang, X., Jia, Z., Yang, J., & Kasabov, N. Change detection in SAR images based on the logarithmic transformation and total variation denoising method. Remote Sensing Letters, 2017, 8(3), 214–223. https://doi.org/10.1080/2150704X.2016.1258125

[16] Gençay, S., & Özcan, C. The Effect of SAR Speckle Removal in SAR-Optical Image Fusion. 2022 30th Signal Processing and Communications Applications Conference (SIU), 2022, 1–4. https://doi.org/10.1109/SIU55565.2022.9864861

[17] Zhou, Z., Li, S., & Wang, B. Multi-scale weighted gradient-based fusion for multi-focus images. Information Fusion, 2014, 20, 60–72. https://doi.org/https://doi.org/10.1016/j.inffus.2013.11.005

[18] Li, S., Kang, X., & Hu, J. Image Fusion With Guided Filtering. IEEE Transactions on Image Processing, 2013, 22(7), 2864–2875. https://doi.org/10.1109/TIP.2013.2244222

[19] Bavirisetti, D. P., Xiao, G., & Liu, G. Multi-sensor image fusion based on fourth order partial differential equations. 2017 20th International Conference on Information Fusion (Fusion), 2017, 1–9. https://doi.org/10.23919/ICIF.2017.8009719

[20] Pajares, G., & Manuel de la Cruz, J. A wavelet-based image fusion tutorial. Pattern Recognition, 2004, 37(9), 1855–1872. https://doi.org/https://doi.org/10.1016/j.patcog.2004.03.010

[21] Liu, Y., Chen, X., Peng, H., & Wang, Z. Multi-focus image fusion with a deep convolutional neural network. Information Fusion, 2017, 36, 191–207. https://doi.org/https://doi.org/10.1016/j.inffus.2016.12.001

[22] Liu, Z., Blasch, E., Xue, Z., Zhao, J., Laganiere, R., & Wu, W. Objective Assessment of Multiresolution Image Fusion Algorithms for Context Enhancement in Night Vision: A Comparative Study. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2012, 34(1), 94–109. https://doi.org/10.1109/TPAMI.2011.109