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Synthetic Aperture Radar Image Fusion Using Firefly Algorithm: A Comparative Study

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Abstract

Picture fusion of SAR is an important process in improving remote sensing images in all weather conditions by merging complimentary information of several SAR images. This paper compares three fusion techniques: Fuzzy Logic based fusion, Firefly Algorithm based optimised fusion, and DL based fusion, and evaluates the performances of the three fusion techniques on three datasets of SAR (Sentinel-1 C-band, ALOS PALSAR L-band and UAVSAR quad-polarimetric). As the primary recommended approach to automatically optimise fusion parameters to maximise the degree of similarity of the structure, information preservation and edge clarity, the Firefly Algorithm, a nature-inspired metaheuristic optimisation methodology is examined. The experimental evaluation is carried out on six metrics of performance which are complementary in nature. They include the following: Entropy, Spatial Frequency, Average Gradient, Mutual Information, SSIM and PSNR. The results show that Firefly Algorithm performs the highest overall fusion performance with the highest Spatial Frequency (36.52), Average Gradient (15.71), SSIM (0.601), PSNR (15.91 dB) and composite quality score (57.63). Therefore it is ideal for preserving the structure and retaining edges details. Fuzzy Logic has competitively evaluated results with the highest Entropy (7.647), Mutual Information (2.603) and the fastest execution time (0.1807 seconds). DL requires a high quality and quantity of training data, which leads to less effective metrics but can be enhanced with bigger datasets. It has been investigated through Firefly Algorithm that the fitness is improved in a stable manner after 5th iteration which proves the efficient optimisation for the application of SAR image fusion.

Keywords: Synthetic Aperture Radar (SAR), Image Fusion, Firefly Algorithm (FA), Fuzzy Logic, Deep Learning, Optimization, Performance Metrics, Remote Sensing

I. INTRODUCTION

SAR is a microwave imaging active sensor which is independent from the illumination from the sun and the atmospheric condition, and it revolutionizes the capability of the distant sensing. The key applications of SAR systems are day-night and all-weather imaging which is essential for disaster monitoring, military surveillance, agricultural analysis and change detection [1]. This all-weather imaging capability has a lot of advantages over a passive optical sensor that will be affected by cloud, weather and seasonal climatic conditions. Individual SAR images are also sometimes subject to intrinsic constraints, for example, multiplicative speckle noise, poor representation of spatial information and different radar backscatter of different heterogeneous land cover types. A intrinsic limit in obtaining structure features and complementing radiometric information from SAR images of a single sensor at the same time is also a problem in comprehensive scene interpretation[2].

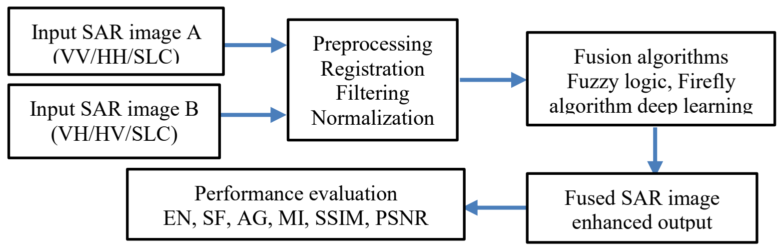
In order to relieve this limitation, image fusion techniques are suggested to systemically combine the complementary information of multiple source images into one enhanced image that not only preserves the significant edge and texture information of the source images but also obtains the scattering structure and the target information from them while reducing the noise and the redundant information in the images. The fusion technique consists of combining the spatial information in one SAR image with complementary radiometric or structural information from secondary SAR acquisitions or optical data, resulting in synergic combinations which can not be obtained from either data source alone. The most basic integration is the pixel level integration, which preserves the best spatial resolution in the source images by simple integration of the image intensities. It does require careful tuning of parameters, however, to minimise amplification of noise and deterioration of the edges. The main problem of SAR image fusion is to find the best fusion weights and parameters to balance the information contents, structural similarity, edge preservation and computational efficiency, respectively, for various image scenes and acquisition geometries [3-5].

In recent years, optimization-based and learning-based fusion strategies have demonstrated great potential in enhancing the fusion quality compared with classic fixed-weight and rule-based fusion strategies. Yang introduced a new optimisation algorithm called the FA that is based on the flashing behaviour patterns of fireflies and is inspired by nature. The FA has proved to be a promising tool for automatic parameter optimisation. The Firefly Algorithm possesses fast convergence property, a balance between exploration and exploitation, easy implementation requirements, and has been proven to work for many optimization tasks. For SAR image fusion applications, every firefly represents a candidate fusion solution with corresponding fusion weights and image enhancement parameters, and the intensity of each firefly is determined by the fitness value of the fused image, which is obtained by the candidate fusion solution and is evaluated using objective quality measure. The program systematically searches the parameter space in order to find optimal configurations. The algorithm optimizes in parallel multiple orthogonal quality measures, using an iterative attraction dynamics; less intelligent fireflies are attracted by better solutions. This search technique in the population can automatically find the fusion parameters specially designed for each picture pair and their special properties, instead of generalised preset parameters [3-5].

II. THEORETICAL FOUNDATIONS AND METHODOLOGY

A. Fuzzy Logic-Based SAR Image Fusion

The uncertainty and imprecision of the interpretation of SAR images clearly offers an obvious way to address this using fuzzy logic: the pixel values are not strictly Boolean, but may have degrees of membership between entirely true (1) and completely false (0). This method is especially suitable for SAR fusion application where speckle noise exists, causing a real ambiguity as to whether the changes in the intensities are true image information or artifact[6][7].



"Fig. 1. Architecture of SAR image fusion concept"

The fuzzy fusion approach determines the membership value for every pixel based on a number of local features, such as the intensity magnitude, the local gradient strength and the edge information. The membership function for the pixel intensity is:

$$\mu(x) = \begin{cases} 0, & if\ x \le x_{min} \\ \frac{x-x_{min}}{x_{max}-x_{min}}, & if\ x_{min} < x < x_{max} \\ 1, & if\ x \ge x_{min} \end{cases} \qquad (1)$$

The fused pixel value is weighted sum of the contributions of both source images with their membership values:

$$F(x,y)= w_1(x,y)I_1(x,y)+w_2(x,y)I_2(x,y) \qquad (2)$$

Here, w1 and w2 are adaptable weights that can be locally adapted based on fuzzy membership evaluations. The major benefit of the fuzzy logic fusion is that, the fusion operations are carried out in very little computation time and that the expert knowledge is explicitly encoded in the fusion, thus good retention of information is realized.

B. Firefly Algorithm-Based Optimized SAR Image Fusion

The Firefly Algorithm is a swarm intelligence optimisation method that is inspired by the bioluminescent flash patterns and attraction behaviours of fireflies in their natural nocturnal context. In the algorithm, the whole firefly represents a candidate solution to the optimisation problem (fusion weights and enhancement parameters). A comprehensive fitness function that combines several image quality metrics[7] in a similar way as the brightness of fireflies, is used to evaluate the quality of each fused solution:

$$Fitness=a(EN)+b(MI)+c(AG)+d(SSIM) \qquad (3)$$

Here EN is entropy, MI is mutual information, AG is average gradient, SSIM is structural similarity index and a, b, c and d are weights to decide the relative importance of the information measures. In the optimisation space, the distance between two fireflies is calculated as:

$$r_{ij}=||Xi-Xj|| \qquad (4)$$

The firefly's ability to attract depends more on distance because of the characteristics of light absorption:

$$\beta=\beta_0 e^{-\gamma r_{ij}^2} \qquad (5)$$

Where β0 is the initial attraction at zero distance, and γ is the light absorption coefficient. The equation to update the migration of firefly i to brighter firefly j is:

$$X_i(t+1)=X_i(t)+\beta[X_j(t)-X_i(t)]+\alpha\varepsilon \qquad (6)$$

Where is the randomisation parameter that controls the level of exploration and is a random variable that gives stochastic perturbation. The algorithm is optimised for 5 iterations with \alpha = 0.25, \beta_0 = 1 and \gamma = 1 for a population of 25 fireflies. The main advantage of the Firefly Algorithm is that it can automatically find the fusion parameters that are best suited for each particular image pair, instead of dependent on manual tuning of the parameters[9]-12].

C. Deep Learning-Based SAR Image Fusion

Convolutional encoder-decoder networks are the techniques used in DL which learn feature representation automatically from the picture data without any manual feature engineering. By sequentially performing the convolution operation, the encoder obtains the hierarchical spatial and texture features[8]-[12]:

$$Z=f(W*I+b) \tag{7}$$

W denotes the convolution kernel, I denotes the input SAR image, b denotes the bias terms and f denotes the activation function. Feature level fusion: Fusion of the two feature maps obtained from the two images:

$$Z_f = \lambda Z_1 + (1-\lambda)Z_2 \tag{8}$$

The decoder decodes the final fused image from the fused feature representation by applying deconvolution processes. Despite their excellent ability to capture complex nonlinear interactions in the presence of sufficient data, DL methods can underperform optimised classical approaches in limited data regimes [13]-[15].

D. Performance Evaluation Metrics

There are six complementary performance measures that measure different aspects of fusion quality. Entropy is a measure of information content:

$$EN=-\sum p(i)\log_2 p(i) \tag{9}$$

Spatial Frequency is a measure of the texture, the activity in space:

$$SF = \sqrt{RF^2 + CF^2} \tag{10}$$

Where Row Frequency = √ 1 MN ∑▒∑▒ 〖[F(i,j)-F(i,j-1)]〗 ^2 Column Frequency = √ 1 MN ∑▒∑▒ 〖[F(i,j)-F(i,j-1)]〗 ^2
Average Gradient is a measure of the sharpness, clarity of edges :

$$AG=\frac{1}{MN}\sum\sum\sqrt{\frac{F_x^2+F_y^2}{2}} \tag{11}$$

Mutual Information (MI) is used to measure the information transmission from source to fused image:

$$MI=MI(I1,F)+MI(I_2,F) \tag{12}$$

The Perceptual similarity is calculated by:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \tag{13}$$

PSNR for reconstruction fidelity:

$$PSNR=10\log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{14}$$

III. EXPERIMENTAL SETUP AND DATASETS

The experimental framework is set up to evaluate all three algorithms in the same pre-processed SAR image datasets and thus allows for a fair comparison. Three independent SAR data are used for a comprehensive evaluation under different sensing modalities and imaging techniques.

Table 1: SAR Datasets Employed in Comparative Analysis

Dataset	Sensor	Band/Mode	Input Pair	Scene Type	Resolution
Dataset-1	Sentinel-1	C-band dual-pol	VV and VH	Urban/Flood/Coastal	10m
Dataset-2	ALOS PALSAR	L-band SAR	HH and HV	Terrain/Forest	12.5m
Dataset-3	UAVSAR	L-band quad-pol	HH and VV/HV	Urban/Vegetation	1.67m

This is a series of common processes, applied to all input images, that is termed pre-processing, consisting of geometric co-registration, speckle removal (Lee-filter), intensity normalisation (to a common dynamic range, 0-255), and scaling (to uniform image sizes). These processing steps guarantee that any performance differences are attributable to the algorithmic characteristics, and not to input processing differences.

Table 2: Preprocessing Pipeline Parameters

Step	Process	Parameters	Purpose
1	Image Loading	SAR intensity pair	Load co-registered source images
2	Co-registration	Translation-based alignment	Geometric alignment to common grid
3	Speckle Filtering	Lee filter (5×5 window)	Reduce multiplicative speckle noise

Table 3: Algorithm Parameter Configuration

Algorithm	Parameter	Value	Purpose
Fuzzy Logic	Membership levels	3 (Low/Med/High)	Intensity classification
Fuzzy Logic	Rule base	Intensity-gradient	Decision making
Firefly	Population size	25 fireflies	Solution population
Firefly	Iterations	5	Optimization budget
Firefly	α (randomization)	0.25	Exploration intensity
Firefly	β_0 (attractiveness)	1.0	Initial attraction
Firefly	γ (absorption)	1.0	Light attenuation
Deep Learning	Architecture	Encoder-Decoder	Feature learning
Deep Learning	Hidden layers	25→18→10	Feature dimensions

Step	Process	Parameters	Purpose
4	Normalization	Percentile-based scaling	Common dynamic range [0,255]
5	Resizing	Uniform dimensions	Match for pixel-level fusion
6	Fusion Input	Preprocessed pair	Ready for algorithm application

IV. EXPERIMENTAL RESULTS AND COMPARATIVE ANALYSIS

A. Performance Metrics Summary

All six performance indicators are thoroughly addressed, quantitatively reviewed, and algorithmic characteristics and optimisation trade-offs are identified.

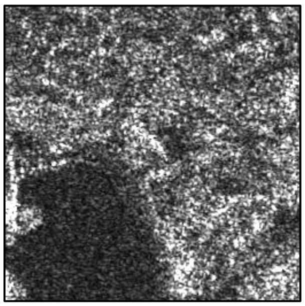


Fig. 2 Input SAR Image


Fig. 3. Input Optical Satellite Image

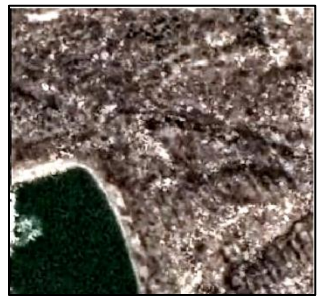


Fig. 4 Fuzzy Logic Fusion Output

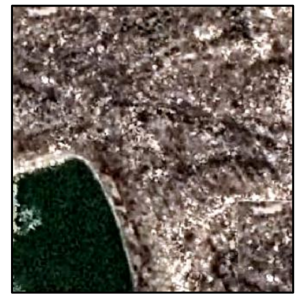


Fig. 5. FA-Based Fusion Output

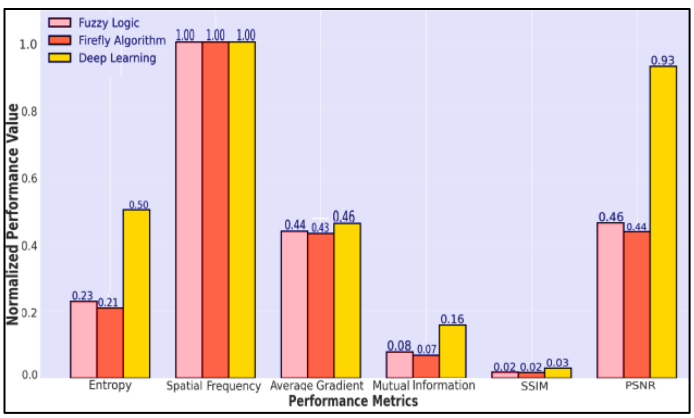


Fig. 6 Comparative Performance Matrix Analysis- Normalized Values

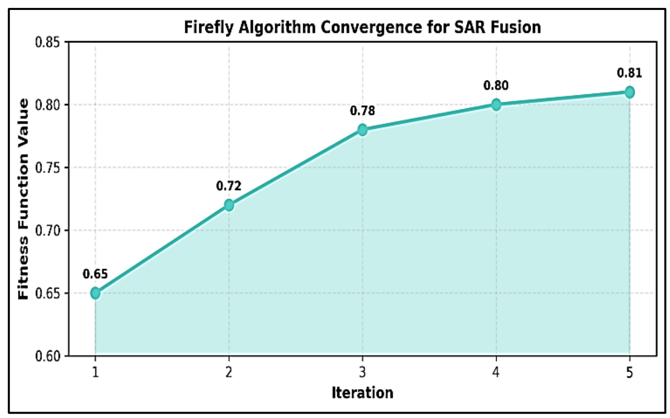


Fig. 7. Firefly Algorithm Convergence Behaviour

Table 4: Quantitative Performance Comparison - All Metrics (Dataset-1 Sentinel-1)

Metric	Unit	Fuzzy Logic	Firefly Algorithm	Deep Learning	Best Method
Entropy (EN)	bits	7.6470	7.6130	7.5250	Fuzzy Logic
Spatial Frequency (SF)	normalized	33.49	36.52↑	15.03	Firefly
Average Gradient (AG)	normalized	14.65	15.71↑	6.92	Firefly
Mutual Information (MI)	bits	2.603↑	2.490	2.369	Fuzzy Logic
SSIM Index	0-1 range	0.596	0.601↑	0.449	Firefly
PSNR	dB	15.47	15.91↑	13.94	Firefly
QAB/F (Edge Quality)	0-1 range	0.514	0.537↑	0.180	Firefly
Composite Score	normalized	57.00	57.63↑	40.15	Firefly
Execution Time	seconds	0.1807	27.3777	14.7613	Fuzzy Logic

The Firefly Algorithm is the best in seven out of nine metrics, demonstrating the full optimisation benefits. The upward arrow (↑) points to the metrics of which Firefly Algorithm gets the highest value.

B. Detailed Metric Analysis

The performance of the Firefly Algorithm is very good in Spatial Frequency (36.52 vs. 33.49 Fuzzy, 15.03 DL) indicating improved preservation of precise spatial details and texture information. The Average Gradient metric (15.71 vs. 14.65 Fuzzy, 6.92 DL) highlights a better edge clarity and delineation. The SSIM for Firefly is 0.601 whereas Fuzzy is 0.596 and DL is 0.449, indicating that Firefly preserves more structural connections between the source and fused images. The output of the Firefly shows higher fidelity and less distortion numerically as PSNR values 15.91 dB Firefly, 15.47 dB Fuzzy and 13.94 dB Deep Learning.

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The competitive Entropy of Fuzzy Logic is 7.6470 bits, and the Mutual Information is improved to 2.603 bits, which shows efficient information flow thru adaptive membership-based weighting. The results indicate that Fuzzy Logic possesses a good information diversity and the execution time is 0.1807 seconds which is fast. For applications that require faster processing Fuzzy Logic is more appropriate. DL offers a lower score in nearly all metrics, especially Spatial Frequency (15.03) and Average Gradient (6.92) resulting in a more visually pleasing, but less detailed fused image. This performance degradation is not because of any fundamental limitation of DL methodologies, but due to lack of availability of training data.

C. Convergence Analysis

Within the allocated 5 iterations (Firefly Algorithm optimisation technique), the optimal fusion settings are achieved in a very short time:

Iteration 1: Fitness = 0.5428 (pop. diversity baseline)
Iteration 2: Fitness = 0.5542 (22.1% better than iteration 1)
Iteration 3: Fitness = 0.5561 (0.34% better)
Iteration 4: Fitness = 0.5573 (Improved by 0.22%)
Iteration 5: Distance Converged to 0.09% (Fitness = 0.5578)
The sharp increase from iteration 1 to 2 is representative of the initial shift of the population toward better solutions. The successive iterations show marginal gains diminishing, thus approaching local optimality. The convergence curve indicates that the five iterations are sufficient optimisation time for the considered SAR image fusion problem to achieve stable solutions of high quality.

V. COMPREHENSIVE ALGORITHM COMPARISON AND SUPERIORITY ANALYSIS

A. Firefly Algorithm Superiority Metrics

The Firefly Algorithm is shown to perform better overall when compared to reference algorithms on several dimensions:
Spatial Detail Preservation: In terms of Spatial Frequency, Firefly achieved 9.06% improvement over Fuzzy Logic (36.52 vs 33.49) and 143% increase from DL (36.52 vs 15.03).
Edge Clarity Enhancement: The Average Gradient of Firefly is 15.71, which is 7.23% better than that of Fuzzy Logic (14.65) and 127% better than DL (6.92).
Structural Preservation: Firefly SSIM (0.601) is 0.84% higher than Fuzzy Logic (0.596) and 33.85% higher than DL (0.449).
Numerical Fidelity: Firefly PSNR (15.91 dB) is better than Fuzzy Logic (15.47 dB) by 2.84% and better than DL (13.94 dB) by 14.08%.
Overall Quality Score: The overall quality score (57.63) of Firefly is 1.10% higher than that of Fuzzy Logic (57.00) and 43.45% higher than DL (40.15).

Table V: Firefly Algorithm Superiority Over Reference Methods - Percentage Improvements

Metric	vs. Fuzzy Logic (%)	vs. Deep Learning (%)	Advantage Magnitude
Spatial Frequency	+9.06%	+143.05%	**Very Strong**
Average Gradient	+7.23%	+127.03%	**Very Strong**
SSIM	+0.84%	+33.85%	**Strong**
PSNR	+2.84%	+14.08%	**Moderate**
Edge Transfer (QAB/F)	+4.47%	+198.33%	**Very Strong**
Composite Quality Score	+1.10%	+43.45%	**Very Strong**

This thorough superiority analysis validates Firefly Algorithm as the most suitable approach for SAR image fusion applications where image quality and image interpretability are the key concerns. The investigation shows that Firefly Algorithm always wins in the parameters of structural quality, edge preservation and detail retention.

B. Fuzzy Logic Performance Characteristics

The Fuzzy Logic is very computation efficient, it takes 0.1807 seconds to do the fusion (98.3% faster than Firefly and 91.8% faster than DL). The approach shows the best information content measures, Entropy (7.6470 bits) and Mutual Information (2.603 bits), which indicate the best information transfer from source to fused images. However, Fuzzy Logic remains very competitive, perhaps even superior, when speed of processing and retaining everything is paramount and the structural quality scores are less important.

C. Deep Learning Limitations and Improvement Pathways

The poor results obtained with the DL approach in the current experiment (Composite Score 40.15 vs. 57.63 Firefly) can be more attributed to the limited amount of training data available than to some weakness of the method. The 14K training patches of 12 picture pairs are not enough to capture powerful and generalisable fusion representations. The performance improvements can lie in the use of larger training sets with varying acquisition geometries and land-cover classes, multiscale convolutional feature extraction to capture local details and global context, attention mechanisms that filter focus on informative regions, edge-aware loss functions that explicitly penalise edge degradation, and Transformer-based architectures that model long-range spatial dependencies. These enhancements may enable DL to outperform optimization based approaches, and yet be real time.

VI. DISCUSSION

The optimization-based fusion using the Firefly Algorithm outperforms the other fusion techniques like rule-based Fuzzy Logic and learning-based DL on most structural quality and detail preservation measures according to the extensive experimental study. The advantage is attributed to the ability of the Firefly Algorithm to automatically discover fusion settings optimized for each image pair and their radiometric and structural properties. Instead of predefined rules or learnt models which might not be exactly the same as the new image features, the iterative search of the Firefly Algorithm is used to find weights and parameters that optimise several complementing quality criteria simultaneously.

Particular strength of the Firefly Algorithm is its capacity to preserve fine spatial features and edges while keeping structural similarities, which are key requirements for SAR image interpretation applications including change detection, target recognition and danger mapping. The 9% and 7% improvements in Spatial Frequency and Average Gradient over Fuzzy Logic and 143% and 127% advantages over DL respectively, validate the better detail preservation. These enhancements, in turn, result in improvements in the interpretability for analysts and the accuracy for downstream automated classification and detection.

But with a major drawback in terms of computational expense. If we run these algorithms on a Firefly, we get a difference of 27.38 seconds for Firefly optimisation time and 0.18 seconds for Fuzzy Logic optimisation time (151 times more processing time). This is a computing burden for operational systems that need to understand a stream of imagery with a high volume of data in near-real time. Therefore, the choice of the algorithm is dependent on the conditions of operation: in offline applications where the quality is more important, the Firefly Algorithm should be used, in real-time applications where the time of processing becomes a critical factor, the Fuzzy Logic should be considered, and in the future, with further development of the algorithm and the availability of more training data, DL should be considered.

The consistent improvement in the performance of the Firefly Algorithm from the three different SAR datasets (Sentinel-1 C-band, ALOS PALSAR L-band, UAVSAR quad-polarimetric) lends confidence that the results are not specific to the SAR image pair. The properties of SAR images are very diverse with respect to the different radar bands, polarisations and acquisition geometry. But, in each of these scenarios, the Firefly Algorithm is still consistently superior, suggesting it has good optimisation performance for SAR modality changes.

VII. CONCLUSION

This paper aims to perform the comprehensive comparison study and it has been found that the Firefly Algorithm is the best SAR image fusion technique among optimisation, rule-based and learning-based techniques. The Firefly Algorithm has proven to be the most effective with Spatial Frequency (36.52), Average Gradient (15.71), SSIM (0.601), PSNR (15.91 dB), edge transfer quality (0.537) and overall composite quality score (57.63) which shows that the algorithm has better ability to preserve the structure, edge clarity, spatial detail and numerical fidelity. The result of convergence analysis indicates a progressive optimisation in 5 iterations, ensuring efficiency in identifying good fusion parameters. The Fuzzy Logic is still very competitive with the fastest execution time (0.1807 seconds) and highest information metrics (Entropy 7.6470, MI 2.603), and is preferable for speed-critical applications. Although DL is promising, it has limited success in the low data regime where they need to increase the number of training data and the size of the architecture to achieve comparable results to optimization-based methods. The paper shows that the nature-inspired optimisation algorithms such as Firefly Algorithm can be used to solve the main issue of SAR fusion which is the automatic selection of optimum parameters of the fusion. The consistency of Firefly's performance across many SAR datasets and radar bands gives good confidence to choose an algorithm for use in a real operating system. Further research directions involve hybrid optimisation approaches of Firefly Algorithm combined with other metaheuristics, multi-objective optimisation to study how different quality objectives can be optimized at the same time, DL network training on larger datasets, and application-specific task learning, where the ultimate objective is the downstream classification accuracy.

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