A Novel Approach for Data Fusion of SAR (EOS-4) and Optical Multispectral (Sentinel-2) Data

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Keywords: EOS-4; Sentinel-2; Data fusion; SAR; Optical MX; Quality Metrics;

Abstract

Current Remote Sensing applications demand multi-source, multi-sensor data fusion. Multi-source, multi-sensor data fusion provides useful information integrated for quick and better interpretation, understanding and effective decision-making. Data fusion of Synthetic Aperture Radar (SAR) data of Earth Observation Satellite-04 (EOS-04) and Optical Multispectral (MX) data of Sentinel-2 are current topic of interest in this paper. SAR and Optical MX which includes active and passive remote sensing technologies belong to different mechanisms of wave interaction due to widely separated and non-overlapping regions of the electromagnetic spectrum. In this paper, a novel approach to the re-implementation of Wavelet, Brovey, Fast Intensity Hue Saturation (FIHS), Frequency filtering, and Pure pixel data fusion methods is presented. The presented novel approach emphasises modulation-based fusion technique with proper normalization and scaling of both the input datasets. Fusion results of presented fusion methods are evaluated visually as well as quantitatively with quality metrics. The quality metrics demonstrate the ability of the presented novel approach to fuse optical spectral information into SAR data effectively to generate improved high-resolution SAR-coloured fused products.

1. Introduction

Various data fusion methods have been used in many applications areas in remote sensing such as land use, land cover mapping and monitoring. In general, data fusion can be simply defined as “the combination of two or more different data to produce new data with a greater quality and reliability using certain algorithms” (Bahador Khaleghi, 2013)(Genderen, 1998). The main intention of data fusion is to reach a better description of information containing the accurate data output, by merging and combining multi-sensor data. There are so many data fusion methods and algorithms in remote sensing. The data from various satellites such as Multispectral (MX), Hyper-spectral and Synthetic Aperture Radar(SAR) is used as input for generating different fusion types of products.

In this paper, we have used Synthetic Aperture Radar (SAR) data from EOS-4 and Optical Multispectral (MX) data of Sentinel-2 for fusion (R. Chandrakanth, 2011) (R. Chandrakanth, 2011). Both sensors have their inheriting complementary characteristics. As SAR is an active remote sensing sensor that belongs to the microwave electromagnetic spectrum range (wavelength from ~ 0.1 cm to 50 cm), opticalis a passive remote sensing sensor (needs daylight and cloudless sky for data acquisition) that belongs to visible to thermal electromagnetic spectrum range (wavelength from ~ 0.3μm to 10.0μm). SAR sensor has the capability for all-weather and day and night acquisition. It measures dielectric and physical properties of surface roughness and is also capable of penetrating clouds. On the other hand, Optical sensors measure chemical characteristics and are rich in spectral information. Optical data is much easier to interpret and provides more visual details of the objects, whereas SAR data contains amplitude and phase information of coherent surface backscatters, which enables high-precision measurement of 3-dimensional topography, surface roughness and dielectric properties.

Fused products of SAR and optical MX sensors are useful for several applications to estimate forest biomass (Md. Latifur Rahman Sarker, 2013), extraction of road network (E. Khesali, 2016), water body structure assessment (Xiaohong Xiao, 2020), land use, land cover classification.

In general, remote sensing data fusion methods fall under three different categories, the pixel level, the feature level and the decision level fusion methods (F. Liu, 2006). We are referring to only pixel-level fusion methods in this paper. Pixel-level data fusion methods are further divided into three techniques of fusion. They are component substitution, modulation-based and multi-resolution analysis techniques. Pixel-level data fusion methods are mainly emphasizing optical panchromatic (PAN) and multi-spectral (MX) data fusion. The main purpose of pixel-level methods is to generate high-resolution MX fused products with improved spatial, structural, and textural details and preserved spectral information of low-resolution input MX data. Hence the pixel-level data fusion methods are for enhancing input low-resolution MX data into high-resolution MX by adopting the high-resolution information from PAN data.

In this paper, our main interest is to enhance high-resolution SAR data information by adopting the spectral information from low-resolution MX data. But when applying the available traditional fusion techniques to the fusion of SAR and optical (MX) data, either spectral features of the optical data or the microwave backscattering information are lost, or both of them are lost simultaneously, which is undesirable. Therefore, it is necessary to develop a novel approach specifically for SAR-optical MXdata fusion methods, which can fully utilize those two types of complementary image information. Given high relevance to SAR and MX data fusion we are presenting a novel approach to implementing Fast Intensity Hue Saturation (FIHS), Brovey, Pure-pixel Frequency and Wavelet methods. These five methods are developed with novel approaches specifically for preserving high-resolution SAR data characteristics and MX data spectral information simultaneously in the fused output products. Hence generation of improved high-resolution SAR data-colored images of False Color Composite (FCC) as fused products is our main interest during this research work.

https://doi.org/10.5194/isprs-annals-XI-3-2026-393-2026

Various SAR and MX data fusion results were generated over different terrains on the earth's surface using proposed methods. Fused products are systematically evaluated through two types of quality assessment approaches, namely qualitative (visual) and quantitative analysis methods. The quantitative analysis is done using statistical parameters (a) without reference parameters Entropy, Standard Deviation (SD), Spatial Frequency (SF) (S. Sahil, 2010) and (b) with reference parameters Signal to Noise ratio (SNR), Peak Signal Noise ratio (PSNR) and Correlation Coefficient (CC)(Samadhan C. Kulkarni, 2020)(Yuhendra, 2018)(Saygin Abdikan, 2012).

The structure of this paper is as follows: Brief Introduction in Section 1, Fusion Methodology overview in Section 2, Novel Approach for fusion methods of SAR and Optical MX Data inSection 3, The study area and datasets are introduced in Section 4. The fused products quality analysis is demonstrated in Section 5. Finally, the conclusion is in the Section 6.

2. Fusion Methodology Overview

Figure 1, depicts the generalized methodology of multi-sensor, multi-source data fusion. There are four major stages of data fusion processing.

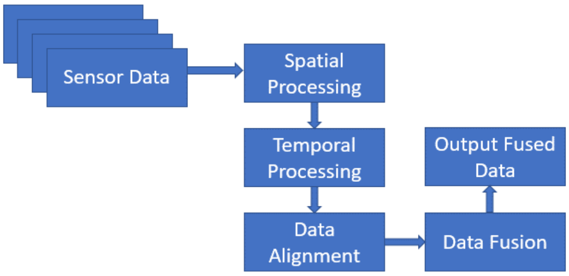

Figure 1. Generalized Methodology of Multi Sensor Data Fusion

2.1 Spatial Pre-Processing:

Disparate and asynchronous data is received from different sources of sensors. Data shall be pre-processed up to sensor sensor-independent level. Sensor-dependent errors shall be corrected. For remote sensing imagery data should be radiometrically and geometrically corrected and resampled into a common pixel grid. Input SAR and MX data must be radiometrically, geometrically corrected and calibrated. Due to side-looking imaging geometry, SAR data suffers imbalance radiometry across the range direction. This radiometric imbalance is corrected using antenna pattern correction. SAR backscattered signal is coherent in nature which causes speckle noise in data. Hence, SAR data must be de-speckled by applying speckle filters like Lee, gamma-map, wavelet filters etc.

2.2 Temporal Processing:

As per the requirement of the intended applications data selection should be at the common timeline. However, datasets should be acquired simultaneously or with less temporal separation to avoid undesirable effects of surface feature changes.

2.3 Data Alignment or Registration:

Registration is a process of geometric alignment of two different images. It is a very crucial step in the fusion process, perfectly registered input SAR and optical MX datasets improve the accuracy of the fusion process. The registration process involves Control Point (CP) identification between the reference and target data either by manual method or automatic method (B. Zitova, 2003) (J. Inglada, 2004). After that transformation and resampling of target data in the reference data pixel grid complete the registration process (P. Suresh Kumar, 2012) (S. Sahil, 2010). SAR images suffer geometric distortions, such as foreshortening, layover and shadow (Wichmann, 1993) (Chen., 2018) (Nidhi Chaubey, 2023). These distortions are more prominent in mountain regions and urban areas with features like tall buildings, bridges, towers etc. All such kind of features appear different in SAR and Optical data and make the registration process more complicated. For automatic registration of SAR and optical MX datasets, the ideal requirements are as follows:

a) Both the inputs should be from the same orbit and pass either ascending or descending orbit.
b) SAR data acquisition should be at higher look angles (~45° to 55°) which minimize geometric distortions.
c) MX data should be nadir-looking.
d) Both the input datasets must be acquired at the same time or with minimum temporal separation.

In an actual scenario getting such kind of data which fulfils all the ideal requirements for perfect registration is very rare. In this paper, the presented SAR and MX datasets are from ascending and descending orbits respectively. All the presented SAR dataset's look angle is around 40°. Temporal separation is also from 10 to 40 days between different SAR and MX input datasets. Hence, in such a scenario manual registration process was preferred. During manual registration, CPs are identified evenly throughout the input datasets. Then registered SAR and MX input datasets are generated.

2.4 Data Fusion Processing:

Cross sensor data fusion processing depends upon algorithms, methods, models and techniques that are going to be used. Different methods are applied to extract information usually depend on the characteristics of the individual sensor data, and therefore may be different if the data sets used are heterogeneous.

3. Novel Approach for Fusion Methods of SAR and Optical MX Data

In this section, each data fusion method is presented in two parts. First part tells the traditional PAN and MX data fusion methods and second part present proposed new method for SAR and MX data fusion. Both the input datasets should be radiometrically, geometrically corrected, calibrated, registered, resampled at same pixel level and scaled perfectly during pre-processing steps before applying any fusion method.

3.1 Fast Intensity Hue Saturation (FIHS) Method:

3.1.1 Traditional IHS method for PAN and MX fusion:

The IHS fusion method utilizes Component Substitution techniques (Genderen, 1998; Zhang, 2010). In this method, multispectral (MX) data are transformed from the RGB (Red-

Green-Blue) color space to the IHS (Intensity-Hue-Saturation) color space (Zhang, 2004). In IHS color space, the “I” component is replaced by high-resolution panchromatic (PAN) data. After this substitution, the IHS color space is transformed back to RGB. As a result, high-resolution fused products of MX data are generated. This method is effective for fusing PAN and MX data.

3.1.2 New Proposed FIHS method for SAR and MX fusion: In the conventional IHS fusion method, the “I” components of SAR and MX datasets are not comparable. Due to differences in imaging mechanisms and the non-overlapping spectral ranges between optical MX and SAR images, the values of “I” in SAR and MX data differ significantly, leading to serious spectral distortion. Consequently, it is inappropriate to use the traditional IHS method directly for SAR and MX data fusion.

To address this issue, we propose the FIHS (Fast Intensity Hue Saturation) method (Te-Ming Tu, 2004; T. M. Tu, 2001). The FIHS method employs a modulation fusion technique rather than the component substitution technique used in the conventional IHS method. The expression for the FIHS fusion is shown in Equation (1), where fusedi is the fused ith band, MXi signifies the ith band of the MX data, μMX is the mean of all the MX bands, and $SynMX_{FIHS}$ is the synthetic band of the FIHS method that modulates the high-resolution SAR data. The term 'SAR' refers to the high-resolution SAR image.

The synthetic band expression for $SynMX_{FIHS}$ is detailed in Equation (2), where μSAR is the mean of the SAR data. One of the advantages of the FIHS method is its ability to use multiple spectral bands for data fusion. Both the SAR and MX input datasets are normalized and scaled using their respective meta-information.

$$\text{fusedi} = (\text{MXi} - \mu\text{MX}) + SynMX_{FIHS} * \text{SAR} \tag{1}$$

$$SynMX_{FIHS} = \frac{\mu\text{MX}}{\mu\text{SAR}} \tag{2}$$

3.2 Brovey Method:

3.2.1 Traditional Brovey method for PAN and MX fusion: Brovey data fusion method was invented by an American scientist(E. Saroglu, 2004). Brovey is a simple method for combining data from different sensors. Brovey method for PAN and MX fusion is a combination of arithmetic operations and normalizes the spectral bands before they are multiplied with the PAN data. This method can also fuse n number of spectral bands. It retains the corresponding spectral feature of each pixel and transforms all the luminance information into PAN data of high resolution (E. Saroglu, 2004) (R. Gharbia, 2014). The formula used for PAN and MX data fusion of the Brovey transform is expressed in equations (3) and (4). In equation (3) fusedi is the fused ith band, MXi is MX ith band, SynMX is the synthetic image of the Brovey method which modulates the high-resolution PAN data, and ‘PAN’ is the high-resolution PAN image. SynMX synthetic image is the average of all the MX bands.

$$\text{fusedi} = \left(\frac{\mathbf{MX}\boldsymbol{i}}{\boldsymbol{SynMX}}\right) * \text{PAN} \tag{3}$$

$$\text{SynMX} = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\mathbf{1}}^{\boldsymbol{n}} \boldsymbol{MX} \tag{4}$$

3.2.2 New Proposed Brovey method for SAR and MX fusion: In the traditional Brovey method, the multiplicative arithmetic operation used for data fusion, the output fused product lost its spectral colour information when input SAR data was used in place of PAN data. Hence, the proposed Brovey transform formula used for SAR and MX data fusion is described in equation (5). In equation (5) fusedi is the fused ith band, MXi is the MX ith band, μMX is the mean of all the MX bands, SynMXBrovey is the synthetic image of the Brovey method which modulates the high-resolution SAR data, and ‘SAR’ is the high-resolution SAR image. SynMXBrovey synthetic image expression shown in equation (6), f is a feature map at the same pixel location p and g is a typical influence function between neighbouring pixels of MX and SAR data respectively.

$$\text{fusedi} = (\text{MXi} - \mu\text{MX}) * \left(\frac{\boldsymbol{SAR}}{\boldsymbol{SynMX\ Brovey}}\right) \tag{5}$$

$$\text{SynMXBrovey} = \boldsymbol{g}\ (\boldsymbol{f}_{\boldsymbol{SAR}}(\boldsymbol{p}), \boldsymbol{f}_{\boldsymbol{MX}}(\boldsymbol{p})) \tag{6}$$

In the proposed Brovey formulation, the function f(p) represents a local feature descriptor extracted at pixel location p, derived from the normalized multispectral (MX) intensity information. In practice, f(p) is implemented as a locally normalized spectral magnitude that captures relative spectral contrast while remaining invariant to absolute radiometric differences between SAR and optical data.

The function g(p, q) denotes a spatial influence function that controls the contribution of neighbouring pixels q within a predefined window centred at p. This influence function is modelled as a distance-weighted kernel, ensuring that nearby pixels contribute more strongly than distant ones. Such spatial weighting helps to stabilize modulation in homogeneous regions while preserving sharp structural variations in urban and man-made features.

The combined use of f and g enables the proposed Brovey method to inject multispectral colour information into high-resolution SAR data in a controlled manner, reducing spectral distortion and avoiding the over-amplification effects typically observed in multiplicative Brovey fusion when SAR replaces panchromatic imagery.

3.3 Pure Pixel Method:

3.3.1 Traditional method for SAR and MX fusion: This method was originally proposed by A. Garzelli(2002) for SAR and MX data fusion over urban areas using the wavelet-based technique (Garzelli, 2002). In this method, output fused image pixels are selected from either SAR data or MX data. The selected pixel was chosen based on the ratio between SAR and MX optical is greater than twice the average ratio over the full image. Traditional SAR and MX images Pure Pixel fusion methodology shown in Figure 2. The ‘LA’ represent low resolution component and ‘LH’,’HL’ and ‘HD’ represent high resolution component. In output fusion results of the traditional method, only manmade objects and other urban structures pixels come from SAR image and remaining information comes from MX images. Means SAR data information is getting lost for other homogeneous regions, which is undesirable for our research work. As mentioned in the introduction section our main interest is to generate a fusion product of high-resolution SAR data information by adopting the spectral information from MX data. To utilize the SAR data characteristics effectively for all the terrain type regions we are proposing the new Pure Pixel method.

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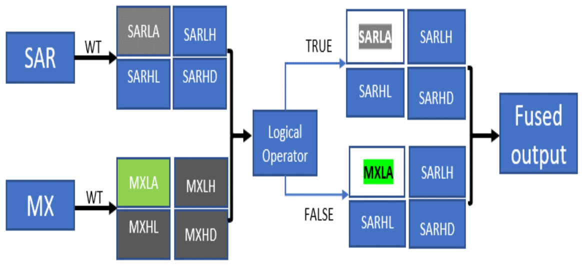

Figure 2. Traditional Pure Pixel Method flow diagram for SAR and MX fusion (low re)

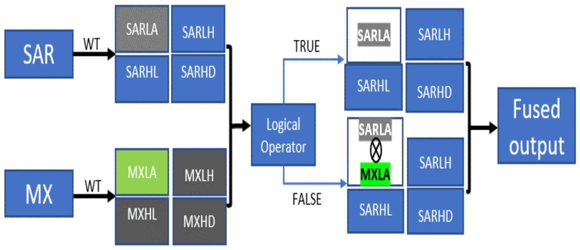

Figure 3. Proposed Pure Pixel Method flow diagram for SAR and MX fusion

3.3.2 New Proposed Pure Pixel method for SAR and MX fusion: In this proposed approach each and every pixel is selected for the regions from the SAR image when the ratio between SAR and MX optical is greater than twice the average ratio over the full image. Otherwise, the SAR and MX images modulated pixel injected into that pixel location of the fused product. The newly proposed Pure Pixel method shown in Figure 3. Fusion products of this method contains point target, manmade objects and other urban structures which gives even bounce signatures are purely from SAR data and the remaining regions contain, modulated optical MX spectral colour information along with textural SAR information.

3.4 Frequency Method:

3.4.1 Traditional Frequency method for PAN and MX fusion: Data fusion methodology of the traditional Frequency method for PAN and MX fusion method shown in Figure 4. First PAN as high resolution and MX as low-resolution data transform into frequency domain and they pass through from high pass and low pass filter respectively. We have implemented the Butterworth filter as a low and high pass filter (S. Butterworth, 1930). Then both the input's filtered frequencies are combined as a component substitution fusion technique. Then inverse frequency transform is applied for fused output image generation (R. Chandrakanth, 2014). In this method high frequency component of the MX image is substituted by high frequency PAN image to generate enhanced high-resolution MX images.

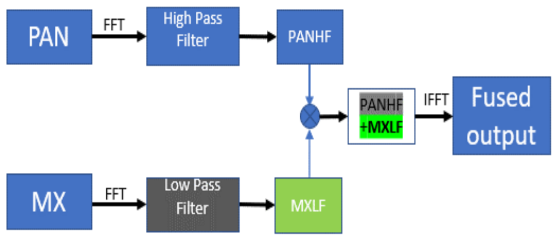

Figure 4. Traditional Frequency Method flow diagram for PAN and MX fusion

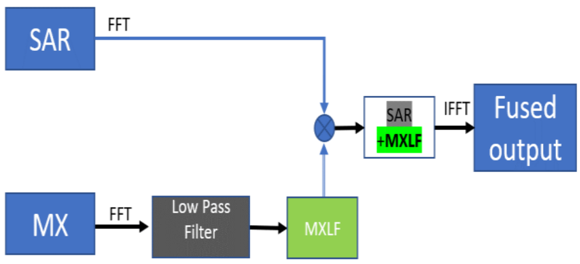

Figure 5. Proposed Frequency Method flow diagram for SAR and MX fusion

3.4.2 New Proposed Frequency method for SAR and MX fusion: SAR images carry information in low-frequency as well as high-frequency components, hence both components are equally important. To keep all frequency component information of SAR data (high and low) as high-priority information, we are not applying any filter to the SAR data. A speckle reduction filter was already applied during the pre-processing step on SAR data. In this method, first both the inputs SAR and MX datasets were normalized and scaled with estimated scale factor using meta information of respective inputs. SAR as high resolution and MX as low-resolution data transform into the frequency domain. A low-pass filter is applied to MX optical images. Then MX filtered spectral frequencies are combined with SAR frequencies for injecting colour information into the fused product. In this proposed method frequency modulation technique is used in place of the frequency component substitution technique. Referring to the typical block diagram of SAR and MX data fusion using the proposed frequency method shown in Figure 5. Finally fused output products are generated after applying inverse frequency transform on the modulated output.

3.5 Wavelet Method:

Multi-resolution or multi-scale methods, such as pyramid transformations, have been used for data fusion since the early 1980s (Mallat, 2008). In 1989, Mallat integrated all wavelet construction methods within the framework of functional analysis. He described the fast wavelet transform algorithm and presented a general method for constructing wavelet orthonormal bases. As a result, wavelet transforms can be utilized for image decomposition and reconstruction (Mallat, 1989; Pajares, 2004; Ma H., 2005; Krista A., 2007; Garzelli, 2002). Wavelet transforms offer a systematic approach to image decomposition, where each level corresponds to a coarser resolution band.

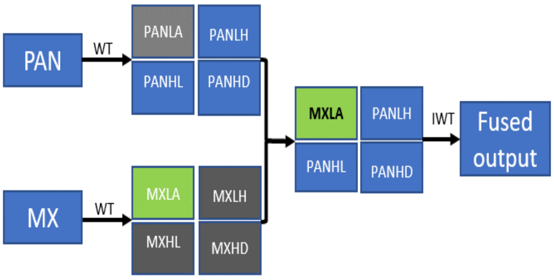

Figure 6. Traditional Wavelet Method flow diagram for PAN and MX fusion

3.5.1 Traditional Wavelet method for PAN and MX fusion: In the case of fusing an MX image with a high-resolution PAN image with wavelet fusion, both PAN and MX images are first decomposed into a set of low-resolution corresponding wavelet coefficients (spatial details) for each level. Each MX image band is then replaced with the low-resolution PAN at the decomposition level. The high-resolution spatial detail is injected into each MX band by performing a reverse wavelet transform on each MX band together with the corresponding wavelet coefficients (Figure 6).

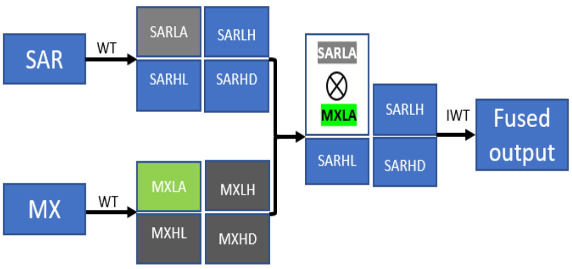

Figure 7. Proposed Wavelet Method flow diagram for SAR and MX fusion

3.5.2 New Proposed Wavelet method for SAR and MX fusion: In the case of SAR high-resolution images decomposed with wavelet transform, the high-resolution coefficient does not carry any significant information as SAR images do not contain sharp edges, boundaries and shape of features like PAN images. Hence, we have proposed a new modulation-based component coefficient generation technique for SAR and MX images using wavelet transform. In this method after wavelet decomposition SAR with MX low-frequency component made a new modulate low-resolution component coefficient which was replaced with SAR low-resolution component. High-resolution fused SAR and MX products were generated by applying inverse wavelet transform. The proposed Wavelet method process diagram is shown in Figure 7.

4. Study Area and Datasets

4.1 Study Area

Datasets covering residential/urban areas, agricultural fields and waterbody regions are used to generate fusion products of different SAR-optical MX fusion methods. The first study area is Mumbai. This dataset has coverage of built-up areas and ocean. The second study site is an agricultural area located in Rajasthan state, India. This dataset consists of vegetation and urban structures (roads and settlements).

4.2 Datasets

The SAR datasets used are EOS-4, FRS1, HH polarized images with a spatial resolution of 3m, SLC level-1 CEOS products. The SAR payload of EOS-04 operating in C-band at a frequency of 5.4 GHz and imaging in both left and right-side looking radar mode. The EOS-04 SAR system has been designed to provide Single, Dual, Full-pol, Hybrid circular polarimetry (Transmit circular, receive linear) data for FRS-1, FRS-2 and for Medium Resolution ScanSAR Mode (MRS) and Coarse Resolution ScanSAR Mode (CRS) modes. For this study, EOS-04 SAR data is indented and downloaded through Bhoonidhi web portal (Bhoonidhi Data hub, 2023).

The optical MX data is acquired from Sentinel-2 European space mission. Sentinel-2 carries an optical instrument payload with Multi-Spectral Instrument (MSI) that has 13 spectral bands: four bands at 10m, six bands at 20m and three bands at 60m spatial resolution. The orbital swath width is 290km. Sentinel-2 provides the Level-1C 100 km2 ortho products in Universal Transverse Mercator (UTM) projection and World Geodetic System-84 (WGS84) datum. Out of 13 spectral bands of Sentinel-2, we have used 3 bands of 10m spatial resolution namely, band-8 spectral bandwidth 760nm-908nm (IR), band-4 spectral bandwidth 646nm-684nm (Red), band-3 spectral bandwidth 537nm-582nm (Green) as False Color Composition (FCC). For this study, Sentinel-2 optical MX data is downloaded through Sentinel Open Data Hub (Hub, 2023).

In the present study, Linear Polarized (HH) fused products are generated using different SAR-optical MX fusion methods. Hence in our data fusion methodology we have taken input SAR EOS-4data as L-2 terrain corrected product and optical MX Sentinel-2 data ortho product respectively.

5. Results Evaluation and Analysis

Evaluation and analysis of fused outputs of proposed novel fusion methods are mentioned in the following sections and the results are presented subsequently.
In this paper work, quality assessment is done by two types of approaches, namely qualitative and quantitative methods. The visual analysis is based on the visual comparison of the color information between the fused image and the original multispectral image (S2A) and that of the spatial details between the fused image and the original SAR image (EOS-4). While visual analysis has limitation due to manual judgment, quantitative analysis based on the evaluation about the spatial and spectral information added to the fused image.

5.1 Study Area-1 (Mumbai):

The Region of Interest (ROI) of SAR image S2A MX (Figure 8) depicts a part of Mumbai city around Chhatrapati Shivaji Maharaj International airport and University of Mumbai. Figure 9a, 9b, 9c, 9d and 9e corresponds to the fused outputs of Brovey, FIHS, Pure pixel, Frequency and Wavelet fusion methods.

5.1.1 Qualitative Analysis:

Visual inspection indicates that all fused outputs (Figure 9a, 9b, 9c, 9d and 9e) are with higher spatial detail compared to input S2A MX product. High ways (roads) and flyovers appear sharper in fused outputs generated by all five methods. Fused outputs of Wavelet and Frequency methods have better spectral content on urban structures and prominent edge details compared to other fusion outputs. Mithi river-course is prominent in all the outputs of fusion methods (Brovey, FIHS, Pure pixel, Frequency and Wavelet) with better contrast. Vegetation at Mumbai University and plantation at airport area appeared comparatively dark in Brovey, FIHS and Pure pixel outputs.

5.1.2 Quantitative Analysis:

The statistical parameters of all the fusion results of Mumbai area is mentioned in Table.1a and 1b in comparison with a reference (S2A MX) image. Entropy value of Frequency and Wavelet outputs is high in compared to all fused outputs and reference S2A multi-spectral image (Table 1a.) indicating information content of output fused data. Increased Spatial frequency is observed in Wavelet output which is responsible for edge details and spatial information. Higher value of SNR and PSNR in FIHS and lower value in Frequency is observed. Similarly high CC values of Frequency and Wavelet output (Table 1b.) indicate better spectral similarity with reference (S2A MX) image but it is less in Pure Pixel and Brovey outputs. Overall, all the statistical measurements indicate that Wavelet output appeared to have better content of spectral information indicated by parameters (Entropy, Spatial Frequency and CC).

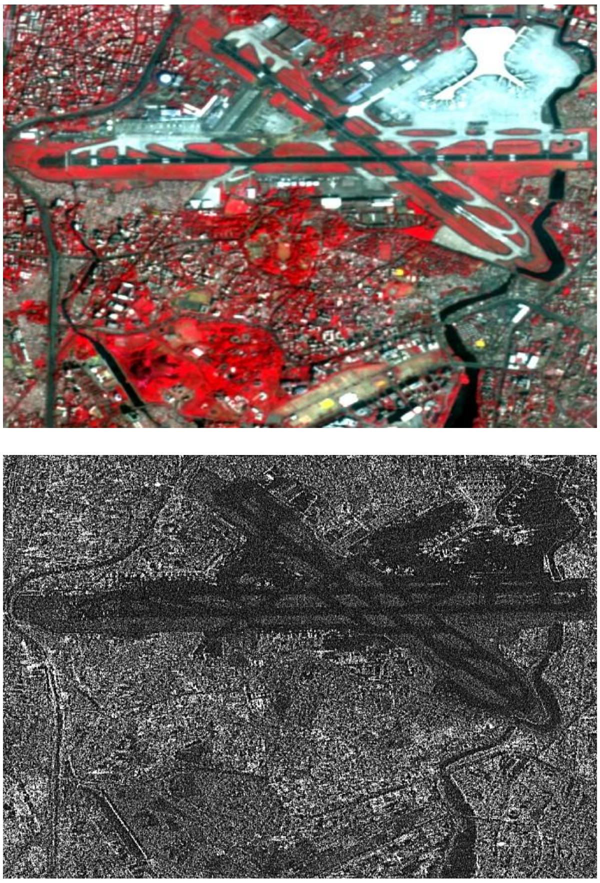

Figure 8. Input S2A MX (top) and SAR (below) of study area-1 (Mumbai)

Figure 9a. Fused products of study area1 by Brovey method.

Figure 9b. Fused products of study area1 by FIHS method

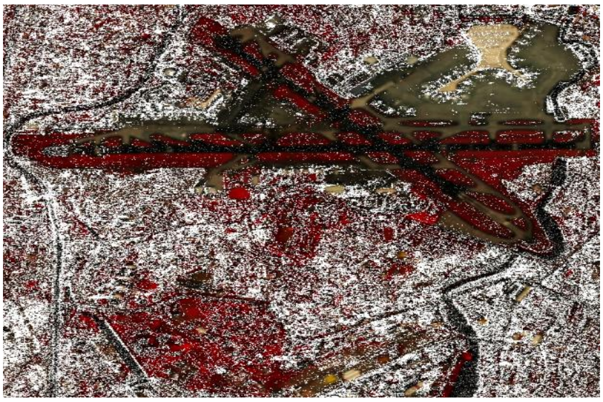

Figure 9c. Fused products of study area1 by Pure pixel method

Figure 9d. Fused products of study area1 by Frequency method

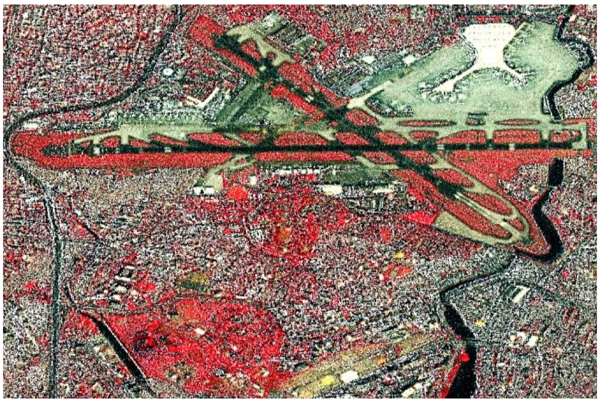

Figure 9e. Fused products of study area1 by Wavelet method

Table 1a. Quality metrics without reference image for study area1 (Mumbai)			
Metric	***Entropy***	***SD***	***SF***
S2A MX	10.189	299.797	2818.74
SAR	11.824	1736.870	3576972.44
Brovey	12.074	1972.935	4635086.17
FIHS	11.955	1740.768	3574258.99
Frequency	13.437	3407.635	10374437.74
Pure pixel	12.194	3114.679	12069738.72
WT	12.503	1910.103	3465003.83

Table 1b. Quality metrics with reference image			
Metric	***SNR***	***PSNR***	***CC***
Brovey	2.825	30.238	0.0398
FIHS	3.46	31.300	0.081
Frequency	1.045	14.721	0.500
Pure pixel	2.0481	25.39	-0.033
WT	2.173	21.776	0.453

5.2 Study Area-2 (Rajasthan):

The Region of Interest (ROI) of SAR image and S2A MX (Figure 10) depicts a part of Rajasthan around agricultural area. Figure 11a, 11b, 11c, 11d and 11e corresponds to the fused outputs of Brovey, FIHS, Pure pixel, Frequency and Wavelet fusion methods.

5.2.1 Qualitative Analysis:

Visual inspection indicates that spatial details are more prominent in all fused outputs (Figure.11a, 11b, 11c, 11d and 11e) compared to input S2A multi spectral product. Roads in between agricultural fields, crop boundaries and small waterbodies appear sharper in fused outputs generated by all the five methods (Brovey, FIHS, Pure Pixel, Frequency and Wavelet). Wavelet and FIHS outputs have better spectral content on crop areas compared to Brovey and Pure Pixel fusion outputs. Visually plantation along the road ways and barren land at agricultural area prominently appeared in Wavelet fusion output compared to Brovey, FIHS and Pure Pixel outputs.

5.2.2 Quantitative Analysis:

The statistical parameters of all fusion results of Rajasthan area are mentioned in Table 2a and 2b in comparison with a reference (S2A MX) image. Entropy value of Frequency and Pure Pixel output is high in comparison to all fused outputs and reference S2A multi-spectral image (Table 2a). Increased Spatial frequency is observed in Wavelet output which is responsible for spatial information. Lower value of SNR and PSNR in Wavelet output is observed indicate images with high noise. High CC values of Frequency and Wavelet output (Table 2b) indicate better spectral similarity with reference (S2A MX) image but it is less in Brovey, FIHS and Pure Pixel outputs. Maximum statistical measurements indicate that Wavelet output appeared to have better content of spectral information (Std. deviation, Spatial Frequency and CC) and spatial details.

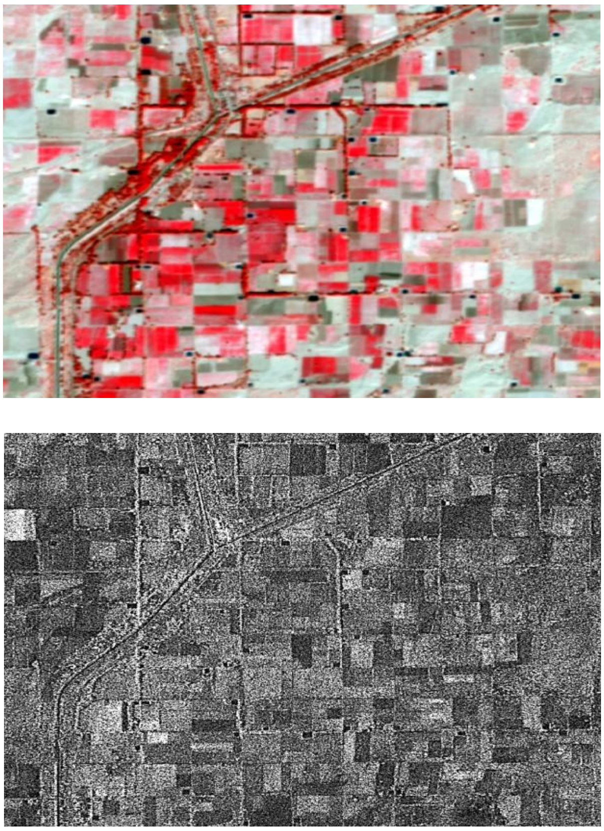

Figure 10. Input S2A MX (top) and SAR(below) of study area-2 (Rajasthan)

Figure 11a. Fused products of study area1 by Brovey method

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
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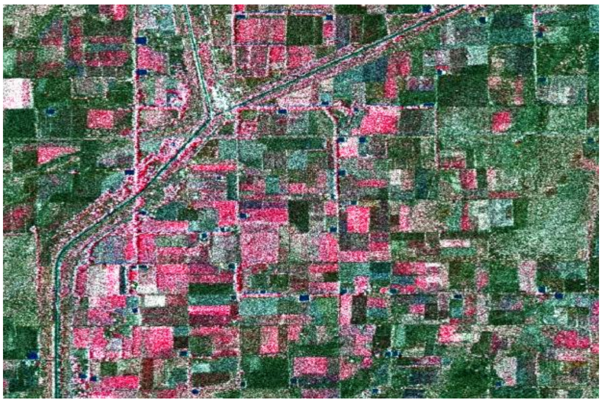

Figure 11b. Fused products of study area1 by FIHS method

Figure 11c. Fused products of study area1 by Pure pixel method

Figure 11d. Fused products of study area1 by Frequency method

Figure 11e.Fused products of study area1 by Wavelet method

Table 2a. Quality metrics without reference image for study area2 (Rajasthan)

Metric	*Entropy*	*SD*	*SF*
S2A MX	10.142	393.190	6893.31
SAR	9.585	226.609	63614.50
Brovey	9.849	285.032	90578.84
FIHS	9.784	259.036	63935.32
Frequency	10.251	347.447	111005.78
Pure pixel	10.500	1256.028	2010644.80
WT	9.852	271.378	61940.38

Table 2b. Quality metrics with reference image

Metric	*SNR*	*PSNR*	*CC*
Brovey	-15.77	25.116	0.059
FIHS	14.142	25.416	0.163
Frequency	3.610	31.92	0.502
Pure pixel	11.356	34.11	0.233
WT	-1.236	29.349	0.533

5.3 Comparative Analysis:

5.3.1 Comparison with recent SAR-optical fusion methods:

Recent advances in SAR-optical data fusion increasingly rely on learning-based frameworks, including convolutional neural networks, autoencoders, and generative adversarial networks. These methods typically aim to learn nonlinear mappings between SAR and optical domains, often requiring large volumes of well-registered training data and significant computational resources. While such approaches demonstrate promising performance for specific applications, their generalization capability across different sensors, acquisition geometries, and geographic regions remains limited.

In contrast, the proposed modulation-based fusion framework employs a physics-aware and data-driven independent strategy. By explicitly preserving SAR backscattering characteristics and injecting optical spectral information through normalized modulation rather than substitution, the proposed method avoids overfitting to specific datasets and remains robust across heterogeneous terrains.

Furthermore, unlike learning-based fusion methods, the proposed approach does not require labelled training samples or sensor-specific retraining, making it more suitable for operational and large-area mapping scenarios where data availability and computational constraints are critical.

5.3.2 Comparison among SAR-optical fusion methods used in this study:

Visual analysis shows that SAR and MX fused output results generated by all the proposed methods (Brovey, FIHS, Pure Pixel, Frequency, and Wavelet) are with higher spatial detail such as urban structures and prominent edge details compared to input S2A MX product. But some of the proposed fusion methods (Brovey, FIHS and Pure Pixel) outputs visually indicate that less preservation of spectral content (appears dark) on some areas/locations on the ground compared to other proposed fusion methods (Frequency and Wavelet) outputs.

Statistical measurements (SNR and CC) indicate Brovey and FIHS fused output results are with more noise and more spectral distortion. Closeness or similarity in structures between the S2A MX and the Pure Pixel output is low indicated by CC value at all study areas. Figure 12, shows plot of Entropy and CC vs. all the Data fusion methods for the two study areas.

Statistical parameters SF and SNR indicate Frequency output is with less spatial information compared to Wavelet method. Wavelet fusion method can effectively avoid the loss of spectral information and spatial information in the fusion process indicated by Entropy, SF, SNR, PSNR and CC. Overall Frequency and Wavelet methods appear to be better with a reasonable performance in different statistical measurements and visual analysis.

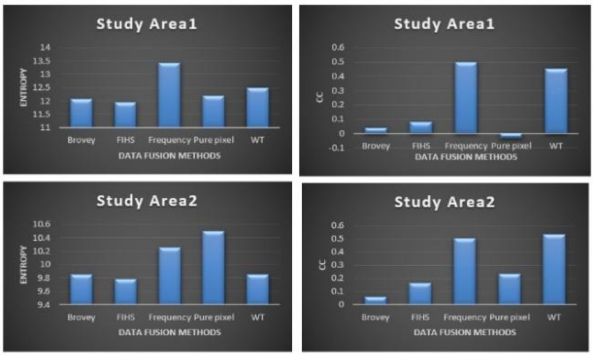

Figure 12 Bar Graph plot of Entropy and CC Vs. all the Data fusion methods for all three-study area

5.3.3 Application-oriented interpretation of fused products:

The proposed SAR-optical fused products offer enhanced utility for several remote sensing applications. In urban environments, improved spatial sharpness from SAR combined with optical colour information facilitates better visual interpretation of road networks, built-up areas, and transportation infrastructure. This is particularly beneficial for urban mapping and infrastructure monitoring under cloud-covered conditions where optical data alone is insufficient.

In agricultural regions, the fusion products enhance field boundaries and crop patterns while retaining spectral contrast related to vegetation health. Such characteristics are valuable for crop monitoring, irrigation assessment, and land-use analysis.

For water bodies and coastal zones, the fused outputs improve the delineation of rivers, shorelines, and small water features by combining SAR sensitivity to surface roughness with optical reflectance information. These properties support applications such as flood mapping, water resource monitoring, and coastal change detection.

Overall, the modulation-based fusion strategy improves interpretability and information content of SAR imagery, thereby supporting downstream remote sensing tasks without requiring task-specific model retraining.

6. Conclusion:

A novel approach for SAR and optical MX data fusion is presented with proposed methods Brovey, FIHS, Pure Pixel, Frequency, and Wavelet in this paper. All the presented methods are re-implemented with new approach to replace component substitution technique into modulation-based technique. To examine performance of all the proposed newly implemented methods results are evaluated by visual and quantitative measurements (Entropy, Std. deviation, Spatial Frequency, SNR, PSNR and CC). Comparative analysis among them is also presented. Quality metric analysis also supports that modulation based fusion techniques are more suitable for SAR and optical MX data fusion. Fusion products retain the spatial information of SAR data and the rich spectral information of MX (visible) data. Hence the proposed novel approach of replacing component substitution data fusion technique by modulation-based analysis data fusion technique with normalized and scaled SAR and optical MX inputs. This proposed approach made optimized use of the complementary information of both (SAR and MX) the sensors to generate a higher quality fused product. SAR-MX fused data product obtain better spatial and spectral information, that helped to reduce the interpretation uncertainty and improves the accuracy related to SAR data. Such value-added products are improving the usability and overall performance of image-based application.

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