1 Adaptive Pansharpening Techniques for High-Resolution Remote Sensing Image Fusion: MRA and Hybrid Approaches

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Abstract

In Earth observation applications, remote sensing image fusion has been proved to be an important means to enhance the spatial and spectral quality of the satellite image. Pansharpening is being developed as an effective method among different image fusion techniques aimed at merging the high spatial resolution panchromatic (PAN) image with the low spatial resolution multispectral (MS) data to produce high-resolution multispectral image. Nevertheless, it is still a huge challenge to obtain a balance between spatial enhancement and spectral preservation in conventional pansharpening methods. In this chapter, an extensive study of adaptive pansharpening techniques for high resolution remote sensing image fusion has been presented with special focus on Multiresolution Analysis (MRA) based adaptive pansharpening and Adaptive Hybrid Pansharpening (AHP) techniques. The proposed MRA-based method uses Gaussian-filter based spatial detail extraction, adaptive intensity estimation using the Levenberg–Marquardt (LM) learning algorithm, covariance-based gain factor computation, and adaptive detail injection to improve spatial resolution while maintaining the spectral information. In addition, an adaptive hybrid pansharpening method based on histogram matching, dual-level high-frequency detail extraction, adaptive fusion parameter estimation and local smoothing operations is proposed to further enhance the fusion effect. To assess this, satellite data representative of various geographical features (e.g., vegetation, water bodies, coastal, and urban areas) from the IKONOS and QuickBird satellites was used in experimental evaluation. The proposed techniques were compared with a few conventional and advanced pansharpening techniques, such as PCA, HPF, FIHS, AWLP, PRACS, conventional hybrid pansharpening and MTF-Wiener filtering. The quantitative results, measured using Relative Average Spectral Error (RASE), Erreur Relative Globale Adimensionnelle de Synthèse (ERGAS), Correlation Coefficient (CC), Average Quality Index (Q-average), and Average Gradient (AG), indicate that the proposed adaptive methods are capable of yielding better spectral preservation, spatial detail representation, and overall fusion quality. The adaptive hybrid pansharpening technique shows the most satisfactory results for both IKONOS and QuickBird data. The proposed adaptive fusion schemes provide efficient and effective image fusion solutions for high resolution remote sensing image fusion and have great potential applications in fields such as urban planning, environmental monitoring, precision agriculture, disaster management, and Earth observation system.

Keywords: Pansharpening, Remote Sensing Image Fusion, Multiresolution Analysis, Adaptive Hybrid Fusion, IKONOS, QuickBird, Spectral Preservation, Spatial Enhancement.

Introduction

Remote sensing is now an essential tool for earth observation, environmental monitoring and management, urban planning, disaster management, agricultural assessment and military surveillance. To obtain detailed information of the Earth's surface, modern satellite imaging systems have to record data in various spectral bands. The main problem, however, is that it is hard to get a high spatial and high spectral resolution image at the same time with a single sensor, because of the physical limitations of the imaging sensor [1, 2]. Multi image fusion is an effective method which fused the complementary information from several images and produced a fused image of good quality and good interpretability.

Pansharpening is one of the image fusion methods that has received much attention for remote sensing applications. Pansharpening aims to merge the high spatial resolution PAN image and low spatial resolution MS image into a high-resolution multispectral (HRMS) image with retaining both spatial and spectral information [3] and [4]. In the last 30 years, many pansharpening methods have been proposed, such as component substitution (CS), MRA, variational optimization and model-based techniques [5]–[9]. Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS), High-Pass Filtering(HPF), and Adaptive Wavelet-based methods are traditional approaches which are computationally simpler; however, they tend to produce spectral distortion and poor spatial detail preservation [3, 6, 9].

In recent years, adaptive fusion methods, deep learning models, and architectures based on Transformer have greatly enhanced the accuracy of pansharpening [18]–[30]. However, the delicate balance between maintaining the fidelity of the spectrum and the enhancement of the spatial structure is a difficult problem. Hence, this chapter focuses on novel adaptive MRA-based pansharpening and hybrid pansharpening techniques for high resolution image fusion in remote sensing and assesses their performances based on the satellite imagery datasets acquired fromIKONOSandQuickBird. The major contributions of this chapter are: (i) a comprehensive review of pansharpening techniques, (ii) detailed analysis of MRA-based adaptive fusion and adaptive hybrid fusion, and (iii) performance evaluation of these techniques by the quantitative metrics like RASE, ERGAS, CC and Q-average.

Fundamentals of Remote Sensing Image Fusion

The term "remote sensing image fusion" is used for the combination of information from several images obtained by various space borne sensors or imaging technology modalities in order to create an image that is more informative and useful. The goal is to take advantage of complementary information in the source images, while avoiding too much redundancy and information loss [5, 11]. Satellite sensors are typically known to generate two types of images: PAN images and MS images. The PAN images have a high spatial resolution but lack spectral information, while the MS images have rich spectral information with relatively low spatial resolution. These two image types are then used along with pansharpening to produce high-resolution multispectral imagery that can be used for advanced applications in remote sensing [4, 8].

According to the fusion method, image fusion techniques can be classified into pixel-level, feature-level and decision-level fusion methods. Of these, pixel level fusion is popular because it retains detailed spatial and spectral information [10, 12]. There are other pansharpening techniques such as CS, MRA, Variational Optimization (VO) and Deep Learning-based methods [9], [15]. The quality of fused images is often evaluated by using quantitative image quality measures like RASE, ERGAS, CC, UIQI and Q-average [9], [12]. These metrics evaluate the quality of the spectrally preserved image, the spatial enhancement and the quality of the image overall, and are used to compare the results of different fusion algorithms.

Literature Review

There are many proposed pansharpening methods for improving fused remote sensing images. The simplicity and low computation complexity of early methods like PCA, IHS and HPF are the reasons why they are widely used [1]–[3]. However, such methods may result in spectral distortions as the spatial data from the PAN image are directly substituted into the MS image [3, 6]. To overcome these limitations, multiresolution approach (MRA) which decomposes the image into low-frequency and high-frequency components has been developed before the fusion process [11, 12].

Adaptive Wavelet based methods showed better spectral preservation than the conventional component substitution methods [4, 11, 15] and ARSIS based fusion showed better spectral preservation than Adaptive Wavelet based methods.It was found that Adaptive Wavelet based methods showed better spectral preservation than the conventional component substitution methods [4, 11, 15] and ARSIS based fusion showed better spectral preservation than Adaptive Wavelet based methods. The performance of the fusion was further enhanced by using the hybrid pansharpening method which brings the benefits of several pansharpening methods together. Chasin et al. proposed adaptive component substitution and hybrid fusion frameworks which could well balance the spatial enhancement and spectral preservation [6] [7].

For the optimization of the extraction of the details and gain estimation during fusion, more recently adaptive injection models and multilevel sharpening techniques have been proposed [13], [14]. Deep learning has caused a great revolution in research related to pansharpening. CNN-based methods, including PanNet, Residual learning networks and target-adaptive CNN methods, demonstrated better fusion results by capturing complex nonlinear relationships between PAN and MS images [16]–[22].

Moreover, transformer-based models like SwinFusion and Vision Transformer Fusion models have shown great potential to understand the long-range spatial relations and boost fusion precision [23]–[27]. There are recent review papers showing that hybrid deep learning and transformer-based image fusion methods are the latest trends in remote sensing image fusion [28]–[30]. However, adaptive MRA-based and hybrid fusion techniques are still interesting because of their low computational complexity, interpretability and applicability in real remote sensing applications.

MRA-Based Adaptive Pansharpening Technique

One of the popular methods to pansharpen is multiresolution analysis due to its ability to maintain the spectral information and enhance the spatial details. MRA-based methods are different from the component substitution-based ones; they are able to extract high frequency spatial information from the PAN image and add it back into theMS image in controlled proportions without direct substitution of spectral components, which may cause spectral distortion [4, 9, 11].

The low-pass Gaussian filter is used to divide the PAN into low-frequency and high-frequency components in the proposed adaptive pansharpening method based on MRA. Its low-frequency component is used for coarse spatial information, and the high-frequency component for edge and texture information which is necessary for the spatial enhancement. The proposed method is adaptive, by which only the relevant high frequencies are injected into the MS image, thus enhancing the spatial resolution without compromising the spectral fidelity.

- **Principle of the Proposed MRA Framework**

  The proposed four main stages are:

  - Pre-processing of the PAN image by applying Gaussian filter for the low frequency components.
  - Inference of a high frequency of spatial details.
  - Adaptive intensity weights estimation based on LM learning algorithm.
  - Adaptive injection of high-frequency details into each spectral band with injection gain factors.

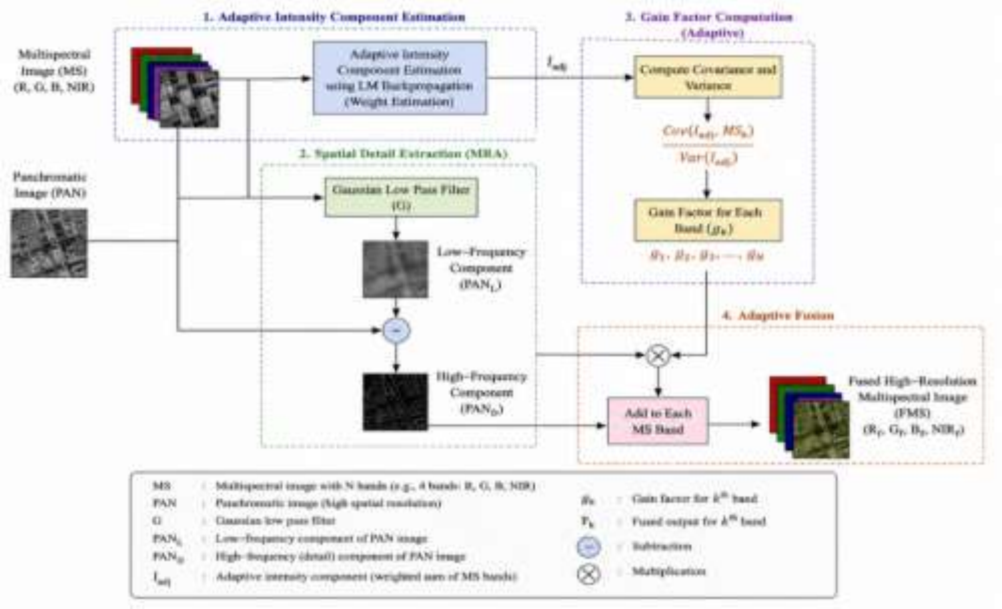

Figure 1: Architecture of the Proposed MRA-Based Adaptive Pansharpening Framework for Remote Sensing Image Fusion

The whole architecture of the proposed method is shown in Figure 1 and the mathematical formulation is described by equations (1) to (5).The Gaussian filter is chosen due to its properties of smoothing while preserving the important image structures and eliminating noise.

- **Extraction of Spatial Details**

  To get the low-frequency component of the PAN image it is convolved with a first-order Gaussian kernel:

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$$\mathrm{PAN}_L(\mathrm{x,y}) = \mathrm{PAN}(\mathrm{x,y}) * \mathrm{G}(\mathrm{x,y,\sigma}) \quad (1)$$

where:

$PAN_L(x, y)$= low-frequency component of the PAN image

$PAN(x, y)$= original panchromatic image

$G(x, y, \sigma)$= Gaussian low-pass filter

σ= standard deviation of the Gaussian kernel

The high-frequency image is then calculated by subtracting the low-frequency image from the original PAN image:

$$PAN_D(x, y) = PAN(x, y) - PAN_L(x, y) \quad (2)$$

where $PAN_D(x, y)$represents the extracted spatial details. The high frequency components are edge information, fine textures and structural features which are later transferred onto the multispectral image. The morphology information obtained is extremely important to increase the spatial resolution of the fused image without losing the spectral information of the multispectral bands.

- **Adaptive Intensity Estimation**

An adaptive intensity component is created from the multispectral image to reduce the spectral distortion introduced during the fusion of the image. The approach proposed here assigns the weights to spectral bands by using LM back propagation algorithm instead of fixed weights.

The weighted intensity part is represented by:

$$I_{adj} = w_1 R + w_2 G + w_3 B + w_4 NIR + b \quad (3)$$

where:

I_{adj}= adaptive intensity component,

R, G, B, and NIRrepresent the red, green, blue, and near-infrared multispectral bands, respectively,

$w_1, w_2, w_3, w_4$are the adaptive weighting coefficients estimated using the LM learning algorithm, and

b denotes the bias term.

The weighting coefficients are updated by the LM optimization algorithm, which minimizes the error between estimated intensity component and the corresponding PANchromatic image response. This adaptive weighting scheme enhances the spectral quality of fused image with reduced color distortion and achieves higher spectral consistency between the PAN and MS images.

- **Gain Factor Computation**

The spatial detail of each of the multispectral bands is adjusted by an adaptive gain factor. The gain factor is calculated from the covariance of the adjusted intensity component and the individual multispectral band.

The adaptive gain factor is expressed as:

$$g_k = \frac{\mathrm{Cov}(I_{adj}, MS_k)}{\mathrm{Var}(I_{adj})} \quad (4)$$

where:

g_k= adaptive gain factor for the k^{th}multispectral band,

I_{adj}= adaptive intensity component,

MS_k= k^{th}multispectral band,

$\mathrm{Cov}(\cdot)$= covariance operator, and

$\mathrm{Var}(\cdot)$= variance operator.

Gain factors specify how much high-frequency spatial information to add to each spectral band during the fusion. The proposed method adaptively controls detail injection by making use of the statistical relationship between the adaptive intensity component and individual multispectral bands. This technique provides effective spatial enhancement and will be minimally distortive spectrally and maintain the original spectral properties of the multispectral image.

- **Adaptive Fusion Process**

Final high resolution multispectral image is obtained by adding the extracted high-frequency component to each of the multispectral bands based on the calculated adaptive gain factor. The fusion process can be written as:

$$F_k = MS_k + g_k \times PAN_D(x, y) \quad (5)$$

where:

F_k= fused output of the k^{th}spectral band,

MS_k= original k^{th}multispectral band,

g_k= adaptive gain factor,

$PAN_D(x, y)$= high-frequency component extracted from the panchromatic image.

The adaptive gain factor is used to set the amount of spatial information sent from the PAN image to each multispectral band. The fusion process, therefore, improves the edge sharpness, texture information and spatial resolution of the input multispectral image, while maintaining the spectral properties of the original image. Moreover, the statistical dependency of the multispectral bands and the adaptive intensity component guarantee balanced intensity enhancement with spatial details and avoids any spectral distortion in the combined image.

- **Advantages of the Proposed MRA-Based Method**

The adaptive pansharpening method proposed in this paper is based on MRA, which has the following advantages:

- Adaptive intensity adjustment resulting in effective spectral information preservation.
- Improved spatial resolution by the detail extraction of Gaussian filtering.
- Less spectral distortion than traditional PCA and IHS methods.
- Adaptive gain computation using covariance statistics.
- Simplicity of computation in comparison with deep learning-based pansharpening methods.
- High resolution satellite imagery with better edge preservation and texture enhancements.

Hence, the proposed MRA framework offers a practical and efficient solution for remote sensing image fusion with a desirable balance between the spectral fidelity and spatial enhancement.

Adaptive Hybrid Pansharpening Technique

The adaptive hybrid pansharpening techniques have merged the benefits of component substitution and multiresolution analysis techniques and provide improved spatial enhancement while retaining spectral fidelity. While the MRA-based methods can preserve the spectral information successfully, there are some parts of spatial information that may not be fully captured in the fused image. This limitation is overcome by hybrid approaches that combine several detail extraction and adaptive fusion mechanisms in one.

The Proposed adaptive hybrid pansharpening approach is based on histogram matching, adaptive high-frequency detail extraction of primary and secondary details, adaptive computation of fusion parameter, and local smoothing operations. The goal is to use only the most relevant spatial information that is available in the panchromatic image in the multispectral image, with minimum spectral distortion.

- **Principle of the Proposed Adaptive Hybrid Framework**

The proposed adaptive hybrid framework consists of the following stages:

- Adaptive intensity component estimation.
- Histogram matching between PAN and MS images.
- Extraction of primary high-frequency information.

- Extraction of secondary high-frequency information using the Laplacian operator.
- Computation of adaptive fusion parameters.
- Estimation of local smoothing factors.
- Adaptive fusion and artifact suppression.

The conceptual architecture of the proposed adaptive hybrid pansharpening framework is illustrated in Figure 2. The framework combines both first-order and second-order spatial details, enabling enhanced edge preservation and improved visual quality in the fused image.The adaptive hybrid framework shown in Figure 2 is mathematically described by Equations (6)–(12).

The suggested adaptive hybrid model is a sequence of the following steps:

- Intensity component estimation (ACE).
- Histogram Matching of PAN and MS images.
- To extract primary high frequency information.
- Secondary high-frequency information extraction with use of the Laplacian operator.
- Adaptive fusion parameters computation step.
- Estimates for local smoothing factors.
- Artifacts suppression and adaptive fusion.

The fusion method is a first-order and second-order spatial fusion method, which can enhance the edge information of the image, enhance the fusion quality of the fused image, and reduce the distortion caused by edge fusion. The adaptive hybrid framework is mathematically represented in Equations (6)–(12) and shown in Figure 2.

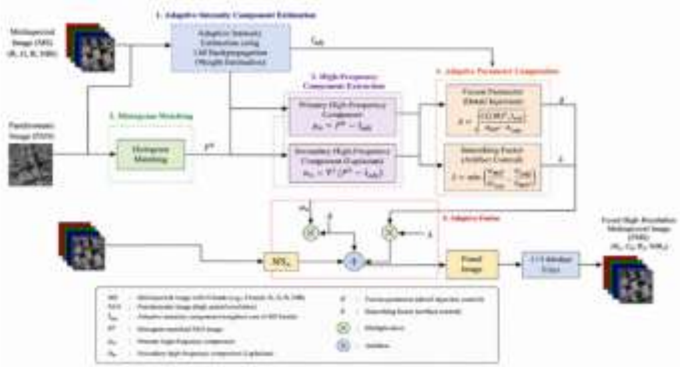

Figure 2. Block diagram of the proposed adaptive hybrid pansharpening framework for remote sensing image fusion

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- **Adaptive Intensity Component Estimation**

Like the MRA approach, an adaptive intensity component is first created from the multispectral image with optimized weighting coefficients derived by the Levenberg–Marquardt learning algorithm.

The adaptive intensity component is given by

$$I_{adj} = w_1 R + w_2 G + w_3 B + w_4 NIR + b \quad (6)$$

where R, G, B, and NIRrepresent the multispectral bands, w_1, w_2, w_3, w_4denote adaptive weighting coefficients, and $b$represents the bias term. The adaptive intensity component is used to obtain better spectral uniformity with the panchromatic image.

- **Histogram Matching**

The multispectral image is first registered to the panchromatic image in terms of a histogram. The histogram matching process reduces radiometric difference between the two image sources and enhances the compatibility between them in the fusion process.

The Histogram matched panchromatic image is represented as"P^h", whereP^h denotes the PAN image histogram matched. The intensity distribution of the panchromatic image is matched to that of the multispectral image prior to detail extraction in the process of histogram matching.

- **Primary High-Frequency Component Extraction**

The main high-frequency information is acquired by subtracting the adaptive intensity component from the histogram matched panchromatic image.

$$\mu_n = P^h - I_{adj} \quad (7)$$

where

μ_n= primary high-frequency component,

P^h= histogram-matched PAN image,

I_{adj}= adaptive intensity component.

The extracted component mainly consists of the dominant components of the edge and texture, which play an important role in the spatial enhancement.

- **Secondary High-Frequency Component Extraction**

To further improve the fine image details, a second-order spatial information is obtained by applying the Laplacian operator to the main high-frequency information.

$$\alpha_n = \nabla^2 (P^h - I_{adj}) \quad (8)$$

or equivalently,

$$\alpha_n = lap(P^h - I_{adj}) \quad (9)$$

where

α_n= secondary high-frequency component,

$lap(\cdot)$= Laplacian operator.

The secondary component focuses on local discontinuities, edges and fine structures, which are not adequately described by the primary high-frequency component.

- **Adaptive Fusion Parameter Computation**

The amount of spatial information that is transferred into the multispectral image can be controlled by the primary fusion parameter.

It is computed as

$$\delta = \sqrt{\frac{CC(MS^l, I_{adj})}{\sigma_{MS^l}\sigma_{I_{adj}}}} \quad (10)$$

where

δ= adaptive fusion parameter,

$CC(MS^l, I_{adj})$= correlation coefficient,

σ_{MS^l}= standard deviation of the multispectral image,

$\sigma_{I_{adj}}$= standard deviation of the adaptive intensity component.

This parameter is adaptively controlled in relation to the local image characteristics, so as to control detail injection.

- **Local Smoothing Factor Estimation**

A local smoothing factor is added to suppress high levels of detail injection and to minimize spectral distortion.

$$\lambda = \min\left(\frac{\sigma_{MS^l}}{\sigma_{I_{adj}}}, \frac{\sigma_{I_{adj}}}{\sigma_{MS^l}}\right) \quad (11)$$

where

λ= local smoothing factor,

σ_{MS^l}= standard deviation of the multispectral image,

$\sigma_{I_{adj}}$= standard deviation of the adaptive intensity component.

The smoothing factor is a dynamic balance between spatial enhancement and spectral preservation.

- **Adaptive Fusion Process**

The multispectral image is then fused with the combined high frequency information (primary and secondary) to produce the final fused image.

$$F = MS_n + \delta\mu_n + \lambda\delta\alpha_n \quad (12)$$

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where

F= fused image,

MS_n= original multispectral image,

μ_n= primary high-frequency component,

α_n= secondary high-frequency component,

δ= adaptive fusion parameter,

λ= smoothing factor.

Finally, the numerical artifacts are eliminated by a median filter to enhance the images visually. The resulting fused image shows improved edge preservation, good spatial details, and minimal variation in spectral distortion.

- **Advantages of the Proposed Adaptive Hybrid Method**

The proposed adaptive hybrid pansharpening technique offers the following advantages:

- Improved spatial enhancement through dual-level detail extraction.
- Effective preservation of spectral information using adaptive intensity estimation.
- Enhanced edge and texture representation through Laplacian-based detail extraction.
- Reduced spectral distortion through adaptive fusion parameter estimation.
- Improved visual quality compared with conventional MRA and component substitution techniques.
- Better adaptability across different remote sensing datasets.

The proposed adaptive hybrid pansharpening approach has the following advantages:

- Better spatial enhancement using two-level detail extraction.
- Adaptive intensity estimation for effective preservation of spectral information.
- Improved edge and texture representation using Laplacian based detail extraction.
- Adaptive Estimation of Fusion Parameters for Reduced Spectral Distortion.
- Better visual quality than conventional MRA and component substitution techniques.
- Improved capability to adapt to multiple remote sensing datasets.

Experimental Setup

High-resolution remote sensing data from the IKONOS and QuickBird satellites were used to evaluate the performance of the proposed MRA-based adaptive pansharpening and adaptive hybrid pansharpening techniques. The selection of these datasets was based on the fact that they offer both PAN and MS images with varying spatial and spectral resolutions, which are appropriate for evaluating the performance of pansharpening methods. The experiment was conducted utilizing representative image sets from both of the platforms, and the effectiveness of the proposed fusion techniques was tested for different images.

- **Satellite Image Datasets**

With this purpose, two popular remote sensing data sets from the IKONOS and QuickBird satellites were used for experimental analysis. To verify the effectiveness of the proposed pansharpening algorithms, representative image pairs of panchromatic and multispectral of various geographical features were selected.

A representative set of multispectral and panchromatic image pairs from the two satellite sensors IKONOS and QuickBird were used for the experimental evaluation. The datasets selected cover a wide range of land-cover features such as vegetation, water bodies, road networks and urban areas, allowing for a detailed evaluation of pansharpening capabilities. The satellite image data used in the experimental study is summarized in Table 1.

Table 1: Summary of Satellite Image Datasets Used in the Experimental Study

Dataset ID	Satellite	Scene Description
IKONOS-1	IKONOS	River and vegetation region
IKONOS-2	IKONOS	Urban and water body region
QB-1	QuickBird	Coastal area
QB-2	QuickBird	Urban landscape

The multispectral images are comprised of Red (R), Green (G), Blue (B), and Near-Infrared (NIR) bands and the panchromatic images offer more high-resolution data. The datasets include various land cover features, including vegetation, water bodies, road networks, and urban structures, which can be used to assess the performance of the fusion.

- **Implementation Environment**

The proposed algorithms have been coded and tested in MATLAB. The MRA-based method is based on Gaussian filtering, adaptive intensity estimation, computation of gain factor and detail injection, while the adaptive hybrid method is based on histogram matching, primary and secondary high frequency extraction, adaptive estimation of the fusion parameter and local smoothing operations. In both cases the same experimental conditions were used for the evaluation to allow a fair comparison between the two methods.

- **Comparative Methods**

The following widely used pansharpening techniques were used as a comparison to the proposed ones:

- Principal Component Analysis
- High Pass Filtering
- Fast Intensity Hue Saturation (FIHS)
- Additive Wavelet Luminance Proportional (AWLP)
- PRACS ((Partial Replacement Adaptive Component Substitution)
- Existing Hybrid Pansharpening
- Modulation Transfer Function (MTF)-Wiener Filtering

The comparison helps to evaluate the proposed techniques in comparison with traditional and advanced pansharpening techniques.

- **Performance Evaluation Metrics**

Widely accepted image fusion metrics are used to quantitatively assess the quality of the fused images:

- Relative Average Spectral Error
- Relativ Dimensionless Synthetical Error
- Correlation Coefficient
- Average Quality Index
- Average Gradient

RASE and ERGAS are lower for reduced spectral distortion while CC and Q-average are higher for better preservation of spatial and spectral information. The metrics given give objective measures of the quality of fusion that is expected of the proposed methods.

In the latter part of the paper the experiments conducted with the IKONOS and QuickBird data sets are reported and discussed to show how effective the proposed adaptive pansharpening techniques have been. Experimental datasets and Quality Evaluation metrics used in this study are given in Table 2.

Table 2: Experimental Datasets and Quality Evaluation Metrics

Dataset	Scene Type	Bands	Evaluation Metrics
IKONOS	Vegetation, Water Bodies, Urban Areas	R, G, B, NIR	RASE, ERGAS, CC, Q-average, AG
QuickBird	Coastal and Urban Regions	R, G, B, NIR	RASE, ERGAS, CC, Q-average, AG

Results and Discussion

A set of representative satellite image data sets, including IKONOS and QuickBird, were used to assess the proposed MRA-based adaptive pansharpening and adaptive hybrid pansharpening methods. The performance of the proposed methods was compared with some of the conventional and advanced pansharpening techniques such as Principal Component Analysis , High-Pass Filtering, Fast Intensity-Hue-Saturation, Additive Wavelet Luminance Proportional, PRACS, conventional hybrid pansharpening, and MTF-Wiener filtering. The goal of the experimental study was to evaluate the performance of the proposed methods in retaining the spectral information while improving the details in spatial domain. The effectiveness of the adaptive hybrid approach is verified numerically in Tables 3, 4 and Figure 5.

- **Qualitative Analysis of Fusion Results**

To perform a qualitative analysis of the fusion results.To conduct a qualitative analysis of the fusion results. The fused images presented in Figures 3 and 4 show the effectiveness of the proposed methods using visual inspection. The resulting fused images with the proposed methods have better edge sharpness, object boundaries and representation of textures than the conventional pansharpening methods.

The application of the traditional techniques of PCA and FIHS applies the same spatial information from the panchromatic image to parts of the multispectral image, so resulting in noticeable spectral distortion. These techniques provide better spatial resolution, but do not always maintain the original color of the image. Likewise, HPF and AWLP methods are capable of reasonably retaining the spectral information, but are unable to adequately enhance the fine spatial structures.

The proposed MRA-based adaptive pansharpening technique preserves the spectral characteristics well, only injecting the extracted high-frequency information into the image by using adaptive gain control. This results in sharper edges, road networks, vegetation edges and urban structures, while still maintaining natural color representation.

The adaptive hybrid pansharpening technique additionally improves the fusion performance by considering both high-frequency information of the primary sensor and high-frequency information of the secondary sensor. Benefits of the Laplacian-based detail extraction mechanism are sharper edges and better visual contrast in areas with local discontinuities and fine details in the image. Therefore, using the adaptive hybrid method can produce images with better visual quality than the traditional methods and approach based on MRA..

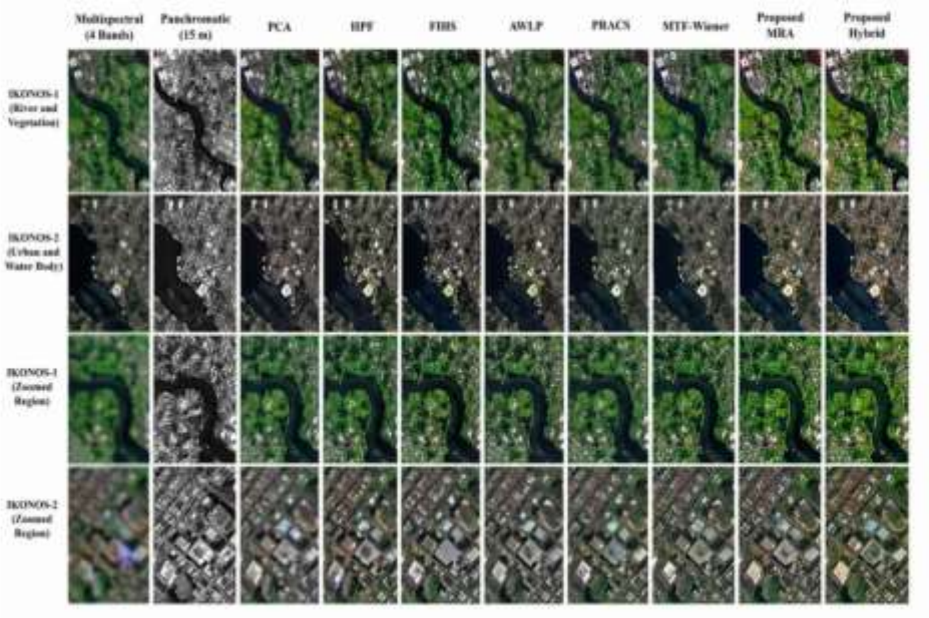

Figure 3: Visual comparison of fused IKONOS satellite images obtained using conventional and proposed pansharpening techniques

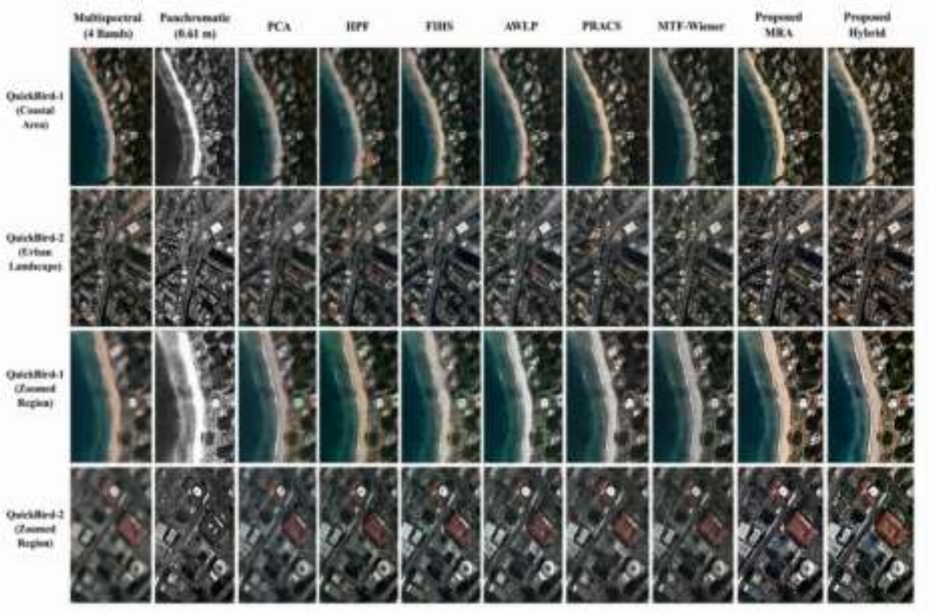

Figure 4: Visual comparison of fused QuickBird satellite images obtained using conventional and proposed pansharpening techniques

- **Results on IKONOS Satellite Images**

The results obtained from the IKONOS satellite images are presented in the following section: The IKONOS data sets include various kinds of geographical features, such as vegetation regions, river network and city structures. These features offer a good set of conditions to test the spectral fidelity and spatial detail preservation capabilities of pansharpening algorithms.

As seen in the visual results, it can be observed that the proposed MRA based method gives sharper object boundaries as compared to PCA, HPF and FIHS. The images are fused to reveal the edges of rivers, sections of roads, and vegetation textures. Moreover, the adaptive gain computation mechanism reduces over-detailed injection of detail, which reduces the spectral distortion.

Additional improvement is obtained by the addition of the second-order spatial details by the adaptive hybrid method. Small features like thin streets and river banks and urban boundaries seem more clearly defined. The fused image has higher spatial resolution and natural color appearance as compared to the original multispectral image. The proposed adaptive hybrid approach outperforms the other techniques such as PRACS and other hybrid approaches in terms of spectral distortion and edge preservation.

Table 3: Quantitative Performance Comparison on IKONOS Images

Method	RASE ↓	ERGAS ↓	CC ↑	Q-average ↑	AG (IKONOS)
PCA	0.7930	18.89	0.6950	0.4997	74.2
HPF	0.3911	8.59	0.9287	0.7016	96.8
FIHS	0.4317	8.35	0.9169	0.7638	102.4
AWLP	0.3977	8.64	0.9145	0.8070	111.6
PRACS	0.6366	7.47	0.7531	0.6684	92.7
Hybrid Pansharpening	0.4216	5.36	0.9258	0.8294	116.3
MTF-Wiener Filter	0.3197	5.07	0.9390	0.8870	127.2
Proposed MRA-Based Adaptive Pansharpening	0.3009	4.60	0.9526	0.9166	136.8
Proposed Adaptive Hybrid Pansharpening	0.2674	4.57	0.9764	0.9568	148.9

Table 3 shows that the proposed adaptive pansharpening methods outperforms the traditional ones for all evaluation measures. The proposed adaptive hybrid pansharpening method has the lowest RASE value (0.2674) and ERGAS value (4.57), both of which are good indicators of spectral preservation. Moreover, it achieves the best CC value of 0.9764 and Q-average value of 0.9568; thus, it has the best spatial enhancement and overall image quality. The proposed MRA-based adaptive pansharpening technique is also competitive and offers significant improvements compared to PCA, HPF, FIHS, AWLP, PRACS, conventional hybrid pansharpening and MTF-Wiener filtering. The results clearly show that the proposed adaptive detail extraction and adaptive fusion parameter estimation can well balance the spatial enhancement and spectral fidelity.

- **Results on QuickBird Satellite Images**

QuickBird images have greater spatial resolution and include more detailed urban and coastal detail. These datasets can be employed to assess preservation of fine structural detail by fusion algorithms.

The experiments show that the proposed methods effectively improve the sharpness of the image without significant spectral artefacts. The proposed approaches maintain the original spectral characteristics better than PCA and FIHS methods. Better spectral preservation with relatively weaker edge enhancement are offered by AWLP and MTF-Wiener filtering.

The adaptive hybrid method achieves the best overall visual performance. Coastal boundaries, road networks and urban structures are more pronounced and lifelike. The dual-level detail extraction mechanism helps to enhance the spatial data quality and the adaptive smoothing factor helps to reduce the artifacts and excess detail injection. As a result the fused images have better visual quality and balanced spectral-spatial features.

Table 4: Quantitative Performance Comparison on QuickBird Images

Method	RASE ↓	ERGAS ↓	CC ↑	Q-average ↑	AG (QuickBird)
PCA	0.5106	12.82	0.8320	0.5161	71.8
HPF	0.3130	5.38	0.9740	0.6387	95.2
FIHS	0.4902	6.48	0.9161	0.7816	101.5
AWLP	0.3768	6.76	0.9318	0.8535	109.7
PRACS	0.6151	5.45	0.5034	0.6033	89.6
Hybrid Pansharpening	0.3677	5.22	0.9152	0.8221	114.1
MTF-Wiener Filter	0.2935	4.77	0.9215	0.9045	124.8
Proposed MRA-Based Adaptive Pansharpening	0.2385	4.60	0.9613	0.9390	135.3
Proposed Adaptive Hybrid Pansharpening	0.2210	4.53	0.9799	0.9756	147.6

The analysis conducted with the datasets acquired from QuickBird satellite further proves the good performance of the proposed adaptive pansharpening methods. The best overall performance is obtained by the proposed adaptive hybrid pansharpening technique with the lowest RASE value (0.2210) and the lowest ERGAS value (4.53), which means that there exist the least amount of spectral distortion. Furthermore, it reaches the peak CC (0.9799) and Q-average (0.9756), having the best spatial enhancement and spectral preservation. The proposed adaptive pansharpening technique based on MRA is also shown to be consistently better than the conventional techniques like PCA, HPF, FIHS, AWLP, PRACS, conventional hybrid pansharpening and MTF Wiener filtering. The results confirm the effectiveness of adaptive intensity estimation, adaptive gain computation, and dual-level detail extraction on enhancing the quality of the remote sensing image fusion.

- **Quantitative Performance Evaluation**

Relative Average Spectral Error, Erreur Relative GlobaleAdimensionnelle de Synthèse, Correlation Coefficient, Average Quality Index and Average Gradient were used in the quantitative evaluation. The smaller the values of RASE and ERGAS, the better the spectral preservation, while the larger the values of CC, Q-average, and AG, the better the spatial enhancement and fusion quality.

The proposed MRA-based adaptive pansharpening method is consistently able to outperform the conventional component substitution and multiresolution-based pansharpening in terms of spectral distortion as demonstrated in Tables 3 and 4 and illustrated in Figure 5. The adaptive gain-based detail injection mechanism is an effective way to transfer the spatial information from the panchromatic image to very well maintain the spectral characteristics of multispectral bands.

In addition, the proposed adaptive hybrid pansharpening approach performs the best overall for both IKONOS and QuickBird data sets. The proposed hybrid method gives the best RASE (0.2674), ERGAS (4.57), and the highest CC (0.9764), Q-average (0.9568), and AG (148.9) for the IKONOS dataset. In a similar way, for the QuickBird data set, the proposed hybrid method provided the minimum RASE value (0.2210), ERGAS value (4.53), and the maximum CC value (0.9799), the Q-average value (0.9756), and the AG value (147.6). These results show the better preservation of spectral information, detailed representation in space, and overall better fusion quality.

The proposed methods innovatively integrate adaptive intensity estimation, adaptive fusion parameters computation, and dual-level spatial detail extraction, allowing for an effective balance between spectral fidelity and spatial enhancement. Thus, the proposed adaptive hybrid method outperforms PCA, HPF, FIHS, AWLP, PRACS, conventional hybrid pansharpening and MTF-Wiener filtering techniques.

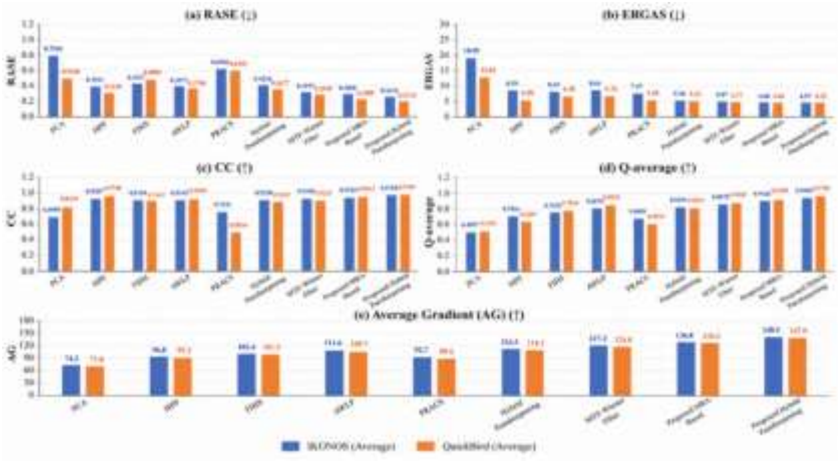

Figure 5: Comparative performance analysis of pansharpening algorithms using RASE, ERGAS, CC, Q-average, and AG metrics.

- **Discussion**

The experimental results validate that adaptive detail extraction and gain estimation are important factors in the improvement of pansharpening performance. The MRA-based approach is able to retain the spectral information, while improving the spatial resolution. However, the adaptive hybrid technique offers extra benefits due to its dual-level detail extraction and adaptive smoothing operations.

The better performance of the adaptive hybrid framework is due to the following reasons:

- Intensity estimation by adaptive method based on LM optimization algorithm.
- Locating the location of specific letters and recognizing letters within text.
- Computation of the fusion parameters and estimation of the smoothing parameter locally.
- Injection of spatial details is balanced in such a way that it avoids spectral distortion and preserves image structures with minimal image degradation.

These mechanisms all enhance spatial enhancement, minimize spectral distortion and produce visually realistic, fused images. The proposed hybrid method successfully preserved the spectral characteristics, while simultaneously improving edge sharpness, texture information, and fine image structures, as evidenced by the higher CC, Q-average, and AG values acquired. Thus, the proposed adaptive hybrid pansharpen image fusion technique is a powerful and effective approach for applications such as high-resolution remote sensing image fusion.

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Applications of Pansharpening

Performing pansharpening is a key step in remote sensing applications of today's sensors, which is based on the high spatial resolution of the panchromatic data and the rich spectral information of the multispectral data. The fused images allow for better visual interpretation and analytical capabilities for many EO applications, such as urban planning, monitoring infrastructure, crop assessment, environmental monitoring, disaster management, military surveillance, coastal monitoring, water resources management, geology and precision mapping. The use of pansharpened images enables the correct identification of roads, buildings and land use patterns in urban applications and crop classification, vegetation monitoring, irrigation management and estimation in agriculture. Better monitoring of deforestation, wetland modification, flood coverage, wildfires and other environmental adjustments are useful for environmental and disaster management applications. The proposed adaptive pansharpening (APS) and AHP methods based on MRA can effectively help these applications by retaining spectral fidelity and enhancing spatial details for reliable and accurate remote sensing analysis and decision making process.

Future Research Directions

Despite significant advances in the field of image fusion by remote sensing, there are still many problems to be solved in developing pansharpening algorithms that can maintain spectral information and enhance spatial details in a variety of imaging conditions. Future studies are likely to explore advanced deep learning algorithms, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and transformer-based models, to enhance fusion accuracy and robustness, with a particular emphasis on integrating adaptive fusion methods with these sophisticated models. The development of lightweight algorithms and low computational power usage for real-time processing on edge devices, UAVs, and onboard satellite platforms is another area of research focus. Moreover, the use of hyperspectral image fusion, artificial intelligence-based optimization methods, reinforcement learning, swarm intelligence and multi-sensor fusion (optical, radar, thermal, hyperspectral) is anticipated to have a key contribution in future Earth observing systems. Therefore, future pansharpening studies will likely focus on intelligent, adaptive, and data-driven pansharpening approaches that enable better spectral fidelity, spatial enhancement, computational efficiency, and applicability to various remote sensing applications.

Conclusion

In this chapter, a comprehensive study of adaptive pansharpening methods for high-resolution remote sensing image fusion has been presented, paying special attention to MRA-based adaptive pansharpening methods and adaptive hybrid

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pansharpening methods. The basic principle of remote sensing image fusion, current pansharening techniques and recent advances in the field of adaptive fusion techniques were discussed.

The proposed MRA based adaptive pansharpening technique includes spatial detail extraction by Gaussian filter, adaptive intensity estimation by Levenberg–Marquardt learning algorithm and computation of the gain factor using the covariance. It is able to effectively enhance the spatial resolution without degrading the spectral information. In addition, the proposed adaptive hybrid pansharpening framework introduces a histogram matching, dual-level high-frequency detail extraction and adaptive estimation of fusion parameters to further enhance the fusion quality, as well as local smoothing operations.

Representative IKONOS and QuickBird satellite data were used for experimental evaluation. The quantitative metrics such as RASE, ERGAS, CC, Q-average and AG were used to evaluate the proposed methods with several conventional pansharpening techniques like PCA, HPF, FIHS, AWLP, PRACS, conventional hybrid pansharpening, and MTF-Wiener filtering and it was found that the proposed methods show better performance than these conventional pansharpening methods. The adaptive hybrid pansharpening technique was the one that had the best overall performance among all the techniques evaluated, with lower spectral distortion, higher correlation, image sharpness and visual quality.

The results verify that adaptive intensity estimation, gain computation and dual-level spatial detail extraction are the main factors affecting the pansharpening performance. Thus, the proposed adaptive hybrid pansharpening method is a powerful and efficient approach for high-resolution remote sensing image fusion and has a great potential for further remote sensing, environmental monitoring, precision agriculture, urban planning and Earth observation applications.

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