Particle Swarm Optimization-Based Multispectral Image Fusion for Minimizing Spectral Loss

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***Abstract* – A novel multispectral image fusion technique is proposed which minimizes the spectral loss of fused product using a proper objective function. It is found that the Relative Average Square Error (RASE) is a good choice to be considered as the objective function. A linear combination of multispectral bands is calculated in which the weights are optimized using particle swarm optimization algorithm. Several experimental studies have been conducted on three public domain datasets to show the effectiveness of the proposed approach in comparison with state-of-the-art methods. The objective and visual assessments of the proposed method support the claims provided in this paper.**

***Index Terms* – Pansharpening, particle swarm optimization, optimal weights, image fusion, panchromatic, multispectral.**

I. INTRODUCTION

Remote sensing data analysis is a field of study which focus on earth0moitoring application like land cover classification [1], target detection [2], and hyperspectral data segmentation [3]. To do these task better, one of the baseline steps is pansharpening. Pansharpening aims at fusing the spectral and spatial attributes of remote sensing data into one single image. Specifically, earth observation satellites can capture two types of data at the same time to keep the Signal-to-Noise Ratio (SNR) at a specific level: (1) PANchromatic (PAN) data which has the highest spatial information of the earth surface and has no color information, and (2) MultiSpectral (MS) data which is the reference of spectral information of the same scene.

As explained in a wide range of previous works and a review study which was conducted by Ghassemian [4], pansharpening methods mainly categorize into three main groups [5]: (1) Component Substitution (CS) methods, e.g. [6], [7], (2) Multi-Resolution Analysis (MRA) techniques, e.g. [8], [9], and (3) Model-Based (MB) approaches [10]. In the first group of image fusion methods, generally a linear combination of Low Resolution MS (LRMS) bands are computed first to estimate the low frequency content of PAN image and then a high frequency detail map is obtained by subtracting from the PAN image. Then, the calculated primitive detail maps are injected into the LRMS bands by considering proper injection gains. A number of improvements have been developed in order to get better fusion performance. For example, Azarang et al. [11] considered optimal injection gains when combining LRMS and PAN edge detectors applied on primitive detail map. In the second category of image fusion approaches, the detail maps of spectral bands are directly computed from the PAN image by applying different transformations into the PAN image to achieve the low frequency information. It has to be mentioned that the CS-based methods are not well performing in spectral domain and MRA-based techniques suffer from spatial distortion. The third group of pansharpening methods, namely MB-based approaches, try to model the pansharpening problem as an optimization problem in which the model is normally considered to be Bayesian.

The idea of deep learning was first introduced by Hinton et al. [12]. Recent improvements in deep learning and machine learning areas have witnessed an indicative improvement in remote sensing applications [13-16]. In particular, for image fusion problem, Huang et al. [17] proposed a new image fusion algorithm using deep neural network. They trained a denoising autoencoder to model the nonlinear relationship between LRMS and High Resolution MS (HRMS) patches. Recently, Liu et al. [18] published a survey on prospective pixel-level image fusion using deep learning architecture.

One of the main shortcomings in the image fusion techniques is employing a proper metric to evaluate the fusion results. Several efforts have been made to model the human perceptual system in terms of objective metrics. Due to unavailability of High Resolution MS (HRMS) image, two general protocols are introduced to solve this issue. In the first protocol [19], the fusion framework is performed in the down-scaled versions of the input data and the original MS data is considered as the reference image. On another hand, in the second protocol, the fusion process is performed in the full-scale scenario and in order to evaluate the fusion results, the no reference quality metrics are employed [20-23].

In this paper, a new framework for pansharpening problem is proposed which is assigned to CS-based category. The idea behind this method is to find a proper objection function to properly estimate the optimal weights of spectral bands of LRMS image when used in the CS-based framework. For this purpose, we select the Relative Average Spectral Error (RASE) metric which can better model the nonlinear relationship between the detail map of CS-based approaches. The extensive experimental studies were conducted to verify the effectiveness of the proposed method in comparison to state-of-the-art method.

The rest of the paper is organized as follows: in section II the mathematical background of the CS-based methods is explained briefly. The framework of the proposed method is also denoted in section II. The datasets as well as the experimental studies have been conducted in section III. The discussion on the fusion outcomes are also drawn in section III. Finally, we conclude the main points of the paper in section IV.

II. MATHEMATICAL BACKGROUND

The general framework of CS-based methods as mentioned in many previous works is as follows:

$$\widehat{\mathrm{MS}}_{\mathrm{k}} = \widetilde{\mathrm{MS}}_{\mathrm{k}} + \mathrm{g}_{\mathrm{k}}(\mathrm{P} - \mathrm{I}) \tag{1}$$

in which $\widehat{\mathrm{MS}}_k$ and $\widetilde{\mathrm{MS}}_k$ are the HRMS and LRMS, respectively, g_k the injection gain corresponds to k-th spectral band, P the PAN image and I is defined as follows:

$$I = \sum_{i=1}^{N} w_i \widetilde{\mathrm{MS}}_i \tag{2}$$

where N denotes the number of spectral bands covering the spectral signature of PAN image and w_i s are the optimal weights of the MS bands which can be calculated using AIHS method [21].

In this paper, we propose to optimize the weights of Eq. (2) by minimizing the following equation

$$\mathrm{RASE} = \frac{100}{M}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\mathrm{RMSE}^2(D_i)} \tag{3}$$

in which M denotes the mean radiance of each spectral band, D_i the detail map of each spectral band. The optimal weights, namely w_i^*, are then used to calculate the final fusion product. The developed multispectral image fusion in this paper is summarized in Fig. 1.

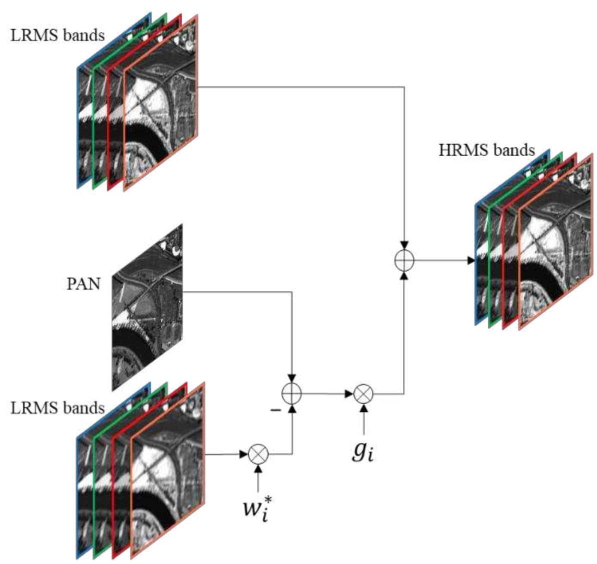

Fig. 1. The proposed fusion framework developed in this paper.

It has to mentioned that the Particle Swarm Optimization (PSO) algorithm is used to compute the optimal weights which is described in [11] in detail. This technique is taken from [23-30] It should be noted that the proposed method has been used in other science such as [30-35] as well. The authors of [35-40] used the same in the field of oceanography and geo-science. More applications of the proposed technique can be found in [40-51].

III. Datasets And Experimental Results

A. *Datasets Used*

In this section, first the details of the datasets employed in this paper are described. Three publicly available datasets from the QuickBird, GeoEye-1 and Pleiades-1A sensors are used to evaluate the proposed method. 4-bands of spectral data, i.e. Blue (B), Green (G), Red (R), and Near Infra-Red (NIR) are available for these datasets. For the QuickBird satellite, the PAN and MS images have the 0.6 (m) and 2.4 (m) resolutions, respectively. In case of GeoEye-1 sensor data, the PAN and MS resolutions are 0.46 (m) and 1.84 (m), respectively. And finally for the Pleiades-1A images, the PAN and MS resolutions are 0.5 (m) and 2 (m), respectively. For the all datasets used PAN and MS images are of size 1024×1024 and 256×256 pixels, respectively.

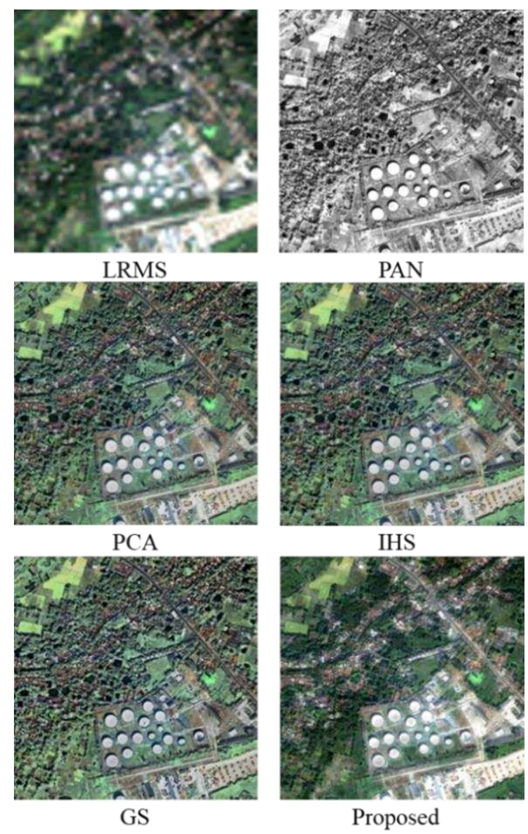

Fig. 2. The fusion results of the QuickBird dataset.

B. *Experimental Results*

In this section, the experiments are conducted on the datasets introduced in previous part. The proposed method is compared with the state-of-the-art methods such as PCA, IHS, and GS methods. In order to assess the fusion outcomes, the Wald protocol is employed [19]. The objective evaluations are conducted using six widely accepted objective metrics namely Erreur Relative Globale Adimensionnelle de Synthese (ERGAS) [4], Spectral Angle Mapper (SAM) [5], Relative Average Spectral Error (RASE) [6], Root Mean Square Error (RMSE) [4], Universal Image Quality Index (UIQI) [23] and Correlation Coefficient (CC) [23].

The ideal value for ERGAS, SAM, RASE, RMSE is zero and the reference value for UIQI and CC is 1. It has to be mentioned that the RASE and ERGAS measure the overall distortion in the fusion product spatially and spectrally. The SAM, RASE, RMSE and CC reports the spectral distortion in the final outcome and UIQI corresponds to the spatial distortion.

In Table I, the optimal weights for each dataset are calculated. It has to be mentioned that for calculating the optimal weights of LRMS bands in Eq. (2), the histogram matching of P and I components was considered. This step is critical since it causes less spectral distortion in the fusion product [45-49].

TABLE I
OPTIMAL WEIGHTS FOR EACH DATASET USED IN THIS PAPER

	w_1^*	w_2^*	w_3^*	w_4^*
QuickBird	0.2978	0.0883	0.0033	0.7616
GeoEye-1	0.0001	0.3775	0.0023	0.4126
Pleiades-1A	0.0001	0.3746	0.3960	0.2533

TABLE II
OBJECTIVE EVALUATION METRICS FOR THE QUICKBIRD DATASET

	ERGAS	SAM	RASE	RMSE	UIQI	CC
PCA	12.894	18.872	48.205	53.716	0.6064	0.5351
IHS	9.1065	9.7916	34.671	38.635	0.7964	0.7842
GS	10.668	14.067	39.954	44.523	0.7110	0.6664
Proposed	**5.8188**	**7.0821**	**22.499**	**25.072**	**0.9168**	**0.9216**
Ideal	0	0	0	0	1	1

TABLE III
OBJECTIVE EVALUATION METRICS FOR THE GEOEYE-1 DATASET

	ERGAS	SAM	RASE	RMSE	UIQI	CC
PCA	5.959	7.8724	21.407	18.484	0.8834	0.8237
IHS	4.541	4.7732	16.801	14.508	0.9282	0.9068
GS	5.050	6.6311	18.249	15.758	0.9135	0.8761
Proposed	**2.508**	**3.3845**	**9.622**	**8.309**	**0.976**	**0.9760**
Ideal	0	0	0	0	1	1

TABLE IV
OBJECTIVE EVALUATION METRICS FOR THE PLEIADES-1A DATASET

	ERGAS	SAM	RASE	RMSE	UIQI	CC
PCA	5.9514	6.1518	24.377	14.315	0.9572	0.9560
IHS	6.1613	5.8765	23.334	13.703	0.9608	0.9524
GS	6.057	5.8088	23.159	13.6	0.9614	0.9547
Proposed	**5.5792**	**4.1949**	**22.158**	**13.012**	**0.9657**	**0.9649**
Ideal	0	0	0	0	1	1

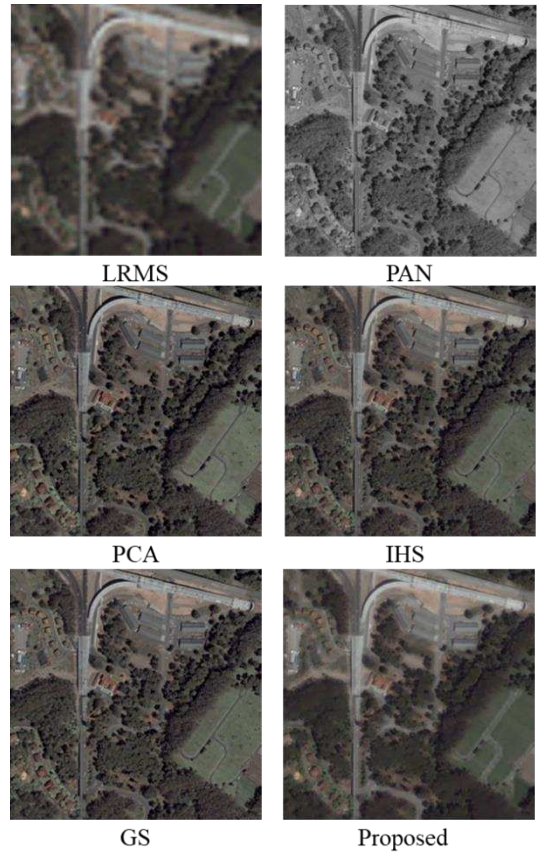

Fig. 3. The fusion results of the GeoEye-1 dataset.

The objective evaluation results of the proposed method as well as the state-of-the-art methods are depicted in Table II through Table IV. As can be seen from these tables, the proposed method performs better especially in ERGAS metric which stands for less overall distortion in the fused product. Not only ERGAS but also other objective metrics can perform better than other techniques which verifies the strength of the proposed approach.

The fusion outcomes for each dataset is reported in Fig. 2 through Fig. 4. As can be understood from these figures, not only the proposed method can perform better in terms of spectral information but also it preserves the high frequency contents of PAN image much better. For example, in Fig. 2, the color of the grass area is better preserved in the proposed approach. As another example, the edges of the white zone in the middle part of the Fig. 4 can be seen more obvious than other fusion methods. These examples provide another demonstration for the generalization capability of the proposed approach against different datasets.

IV. CONCLUSION

A new CS-based image fusion method is proposed in order to enhance the spatial and spectral contents of fusion products. The main idea of the paper is the utilization of proper objection function to calculate the optimal weights of spectral bands. In order to estimate the detail maps properly, the weights of the

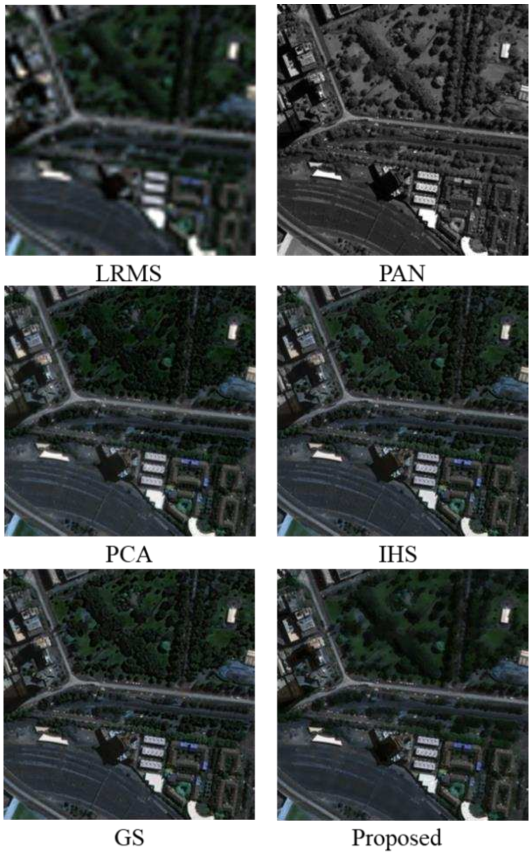

Fig. 4. The fusion results of the Pleiades-1A dataset.

spectral bands are computed using RASE metric. Several experiments on three public domain datasets promoted the claims proposed in this paper.

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