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Modified Synthetic Variable Ratio Pansharpening Method

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Abstract – Pansharpening, which is transferring the spatial content of a high-resolution panchromatic (PAN) band into a lower-resolution multispectral (MS) image to produce a spatially enhanced MS image, has always been one of the hottest topics of image processing. Numerous studies have focused on developing approaches to inject the spatial details with minimum spectral distortion. This study utilized the Genetic Algorithms (GA) to improve the performance of the Synthetic Variable Ratio (SVR), which is one of the most conventional pansharpening methods. This method was modified such that the weight of each MS band was estimated by means of a GA to achieve the optimum result. The spectral quality of the image produced by the proposed approach was compared against those of the images obtained from widely-used pansharpening algorithms Principal Component Analysis (PCA), Modified IHS (MIHS), Gram-Schmidt (GS), Nearest Neighbor Diffuse (NND), High-Pass Filtering (HPF) and conventional SVR. The quantitative evaluation of the pansharpening results revealed that the proposed approach resulted in superior spectral quality, compared to the other methods.

Keywords – *pansharpening, genetic algorithm, synthetic variable ratio, image enhancement, image fusion*

I. INTRODUCTION

The main objective of pansharpening is to inject the spatial characteristics of a higher-resolution PAN band into a lower-resolution MS image. Pansharpened images can be used for further analysis (such as image classification, object recognition etc.) which attaches importance to the performance of the pansharpening methods used. Since there is no such thing as 'the best pansharpening method' in the literature [1], each pansharpening approach is expected to distort the color content of the input MS image to some extent. To achieve the best color fidelity, researchers have put so much effort to develop more effective approaches.

The BRV method is one of the very first pansharpening methods used by remote sensing community. The method multiplies each MS band by the PAN band and divides the result by the intensity produced by summing all input MS bands [2]. The conventional SVR, which is a modified version of the BRV method, calculates the intensity component as the weighted sum of the input MS bands [3], [4]. The PCA method, one of the most fundamental component substitution-based methods, produces outputs by substituting the PAN band by the first principal component of the PCA-transformed image [5]. The GS, similar to the PCA method, replaces the first band of the GS-transformed image by the PAN band in order to produce the pansharpened image [6]. The MIHS method is able to deal with more than three MS bands [7], unlike the conventional IHS-based pansharpening method [8], where an intensity obtained from the IHS transformation of the RGB bands is replaced by the PAN band to transfer the spatial details. The NND method considers each pixel spectrum in the pansharpened image as a weighted linear mixture of the spectra of the neighboring superpixels [9]. The HPF method adds the spatial details of a high-pass filtered PAN image into the input MS image [10].

This study aimed to modify the conventional SVR pansharpening method to improve its spectral quality preservation performance on MS images. Further information on the proposed method can be found in the following section.

II. MATERIAL AND METHODOLOGY

A. Study Area and Data

The study area was selected in the Surmene province of the city of Trabzon, which is located in the northeast of Turkey. All pansharpening approaches used in the present study were employed by using WorldView-2 MS (2 m) image and WorldView-2 PAN (50 cm) bands, which were both acquired in 2012.

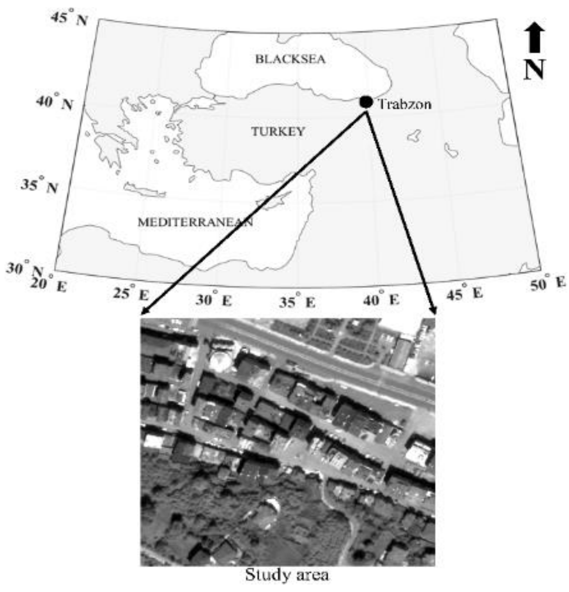

Fig. 1 Study area

B. Modified SVR Approach

The conventional SVR method calculates the pansharpened bands by multiplying each MS band by the PAN band and dividing the result by an intensity band computed as the weighted sum of all input MS bands. The BRV method considers that the weights of all MS bands are equal, which is the main reason for the spectral distortion caused by this method. Hence, more reasonable band weights should be used to compute more efficient intensity components. This study estimated a weight for each MS band by means of the GA.

The GA is a randomized optimization method based on the principles of evolution [11]. It applies a 'survival of the fittest' strategy to find the optimum solution in a very complex environment [12]. The GA starts by generating a population, which consists of randomly generated chromosomes. An objective function is applied on each chromosome and a fitness criterion is specified to evaluate the fitness of each chromosome. The fittest chromosomes are transferred to next generations in order to produce new offsprings via crossover and mutation operations [11], [13]. The selection, crossover and mutation operations continue until the optimum solution is found.

In this study, we encoded a GA in MATLAB environment to estimate the band weights achieving the optimum SVR pansharpening performance. The population size, crossover rate and mutation rate parameters were set to 1000, 0.95 and 0.05, respectively. The objective function was the conventional SVR method itself, whereas The Root Mean Square Error (RMSE) was the fitness criterion. The encoded GA tried to find the chromosome that achieved the minimum RMSE. The iterations revealed that the band weights of 0.16, 0.10, 0.13, 0.14, 0.12, 0.13, 0.12 and 0.09 generated the intensity component providing the optimum pansharpening result for the WorldView-2 data set used.

III. Results and Discussion

Visual inspection of pansharpening results may provide a general overview about the color preservation performances of the methods used. If the color content of a pansharpened image is visually similar to that of the input MS image, then the used pansharpening method can be said to be successful in spectral manner. Figure 2 shows the results of the BRV, PCA, GS, MIHS, NND, HPF, SVR and proposed approaches to compare their results against each other and against the input MS data. As seen in the figure, the proposed approach provided the optimum pansharpening result in terms of spectral quality, as it produced colors that were in best agreement with those of the input MS image. Despite the fact that the MIHS method provided similar colors to the input MS data, it caused a paleness in the pansharpened image. It also caused apparent color distortions in darker areas. The GS and conventional SVR methods were found to be the other ones that produced acceptable results. Figure 2 also shows that the PCA, NND and BRV methods caused significant color distortions in many parts of the study area. When it comes to spatial fidelity, the PCA, MIHS and GS methods were found to be less successful in transferring the spatial details, compared to the other approaches used. In spite of the fact that qualitative evaluation presents a general overview on pansharpening performances, it is highly subjective and therefore cannot be utilized to render a strict decision on spectral quality. Hence, additional quantitative measures are needed for more reasonable spectral quality investigation.

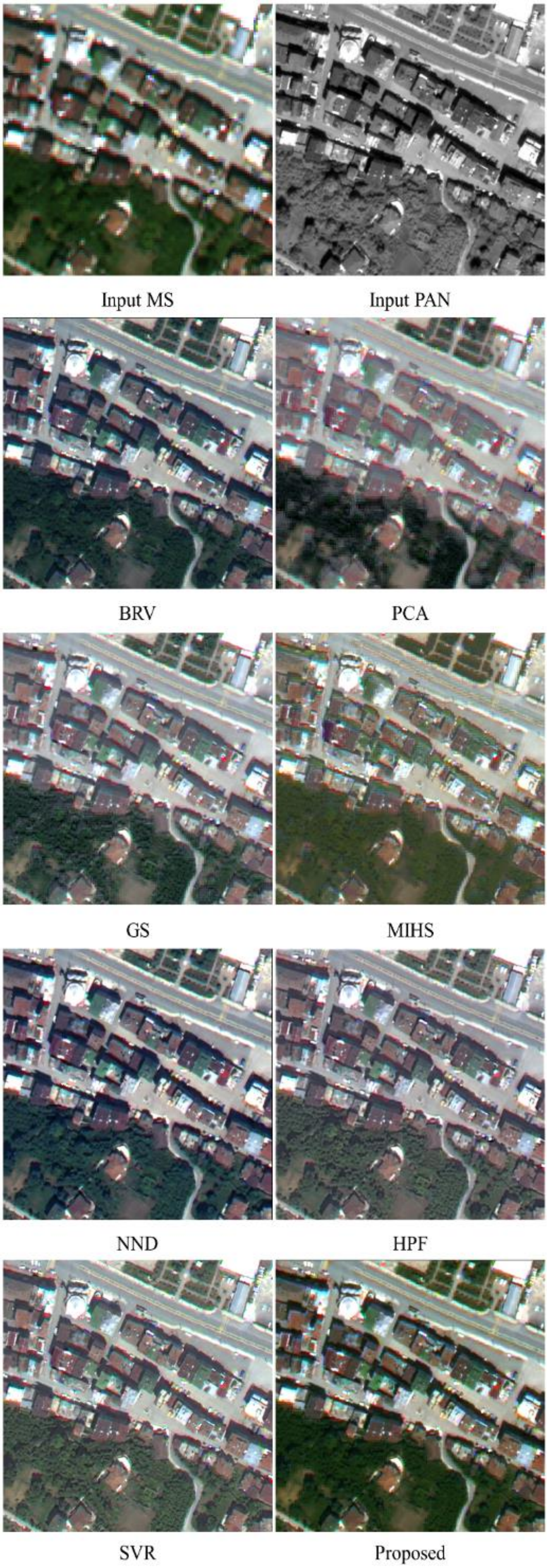

Fig. 2 Pansharpening results

The spectral quality of all pansharpening results were also investigated by means of the Erreur Relative Globale Adimensionalle de Synthese (ERGAS) [14], Structural Similarity (SSIM) [15], Universal Image Quality Index (UIQI) [16], Feature Mutual Information (FMI) [17] and Gradient Similarity (GSM) [18] metrics. The correlation coefficient (CC) was also calculated between the input MS and pansharpened bands to evaluate the color consistency. The best value for the ERGAS metric is 0, whereas 1 for the others. Following is the mathematical theories of the quantitative metrics used.

$$\mathrm{ERGAS} = 100\frac{h}{l}\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{RMSE(k)}{\mu(k)}\right)^2}$$
$$\mathrm{RMSE} = \sqrt{\frac{1}{np}\sum_{i=1}^{np}(MS(k)_i - F(k)_i)^2} \tag{1}$$

$$\mathrm{SSIM} = \frac{(2\mu_{MS}\mu_F + C_1)(2\sigma_{MS-F} + C_2)}{(\mu_{MS}^2 + \mu_F^2 + C_1)(\sigma_{MS}^2 + \sigma_F^2 + C_2)} \tag{2}$$

$$\mathrm{UIQI} = \frac{4\sigma_{MS-F}\overline{MS}\,\overline{F}}{\left(\overline{MS}^2 + \overline{F}^2\right)(\sigma_{MS}^2 + \sigma_F^2)} \tag{3}$$

$$\mathrm{FMI} = \frac{I_{F-MS}}{E_F + E_{MS}} + \frac{I_{F-PAN}}{E_F + E_{PAN}} \tag{4}$$

$$\mathrm{GSM} = \frac{2g_{MS}g_F + C_4}{g_{MS}^2 + g_F^2 + C_4} \tag{5}$$

$$\mathrm{CC} = \frac{\sum_m\sum_n(MS_{mn} - \overline{MS})(F_{mn} - \bar{F})}{\sqrt{\sum_m\sum_n(MS_{mn} - \overline{MS})^2(F_{mn} - \bar{F})^2}} \tag{6}$$

where,
h is the spatial resolution of the PAN image,
l is the spatial resolution of the MS image,
MS is the input MS image,
PAN is the input PAN image,
F is the pansharpened image,
np is the total number of pixels,
K is the total number of bands,
μ refers to mean,
σ refers to variance,
E refers to histogram-based entropy,
I refers to information,
g refers to gradient.

Table 1 shows the metric values calculated to investigate the spectral quality of the pansharpened images. The best metric values are highlighted with grey color in the table. As seen in the table, the proposed approach got the best values from all metrics, except for the FMI. This, of course, led us to the conclusion that the proposed approach provided spectrally superior results compared to the other methods used, which is in good agreement with visual findings. Table 1 also shows that the GS method got the best metric values after the proposed approach. The HPF and conventional SVR methods were found to be other ones that provided images with high spectral fidelity. The MIHS, BRV, NND and PCA presented the least spectral quality preservation performances with respect to the metric values given in Table 1, which is also in conformance with qualitative evaluation results.

One of the biggest advantages of GAs is that they are not dependent on complicated computations, which makes them easy to implement. Estimating a weight for each MS band via GA enabled the generation of a more efficient intensity component and therefore, the preservation of the color content while transferring the spatial details. Increasing the population size may lead to a better color balance between the input MS and pansharpened bands. However, this will cause an increase in computation time.

Table 1. Spectral metric values

Method	ERGAS	SSIM	UIQI	FMI	GSM	CC
BRV	193.137	0.083	0.033	0.888	0.735	0.865
PCA	19.699	0.497	0.262	0.867	0.922	0.859
GS	5.074	0.633	0.325	0.888	0.950	0.895
MIHS	7.549	0.522	0.245	0.860	0.926	0.751
NND	7.228	0.454	0.196	0.857	0.920	0.812
HPF	5.338	0.629	0.305	0.902	0.941	0.877
SVR	5.330	0.615	0.282	0.898	0.946	0.879
Proposed	4.107	0.694	0.433	0.870	0.957	0.904

IV. Conclusion

This study aimed to improve the performance of the SVR pansharpening method by estimating a weight for each MS band via GA. Qualitative and quantitative investigation revealed that the proposed approach did not only surpass the conventional SVR, but also widely-used methods BRV, PCA, GS, MIHS, NND and HPF in terms of spectral quality. Using GA with the SVR method provided an efficient solution to the spectral distortion problem. Further studies will focus on improving the performances of other pansharpening methods with the aid of GAs.

References

[1] C. Pohl, and J. van Genderen, *Remote sensing image fusion: A practical guide*, Crc Press, 2016.

[2] W. A. Hallada, and S. Cox, “Image sharpening for mixed spatial and spectral resolution satellite systems,” in *Proc. 17th International Symposium on Remote Sensing of Environment*, 1983, pp. 1023-1032.

[3] D. Pradines, “Improving SPOT images size and multispectral resolution,” in *Earth Remote Sensing Using the Landsat Thematic Mapper and SPOT Sensor Systems, International Society for Optics and Photonics*, 1986, pp. 98-103.

[4] C. K. Munechika, J. S. Warnick, C. Salvaggio, and J. R. Schott, “Resolution enhancement of multispectral image data to improve classification accuracy,” *Photogramm Eng. Remote Sens.*, vol. 59, no. 1, pp. 67-72, 1993.

[5] P. S. Chavez, and A. Y. Kwarteng, “Extracting spectral contrast in Landsat Thematic Mapper 23 image data using selective principal component analysis,” *Photogramm. Eng. Remote Sens.*, vol. 55, pp. 339–348, 1989.

[6] C. A. Laben, and B. V. Brower, “Process for enhancing the spatial resolution of multispectral imagery using pan-sharpening,” U.S. Patent 6 011 875, Washington, DC: U.S. Patent and Trademark Office, 2000.

[7] *Erdas Imagine Field Guide*, Leica Geosystems.

[8] R. Haydn, G. W. Dalke, J. Henkel, and J. E. Bare, Application of the IHS color transform to the processing of multisensor data and image enhancement. In *Proc. International Symposium on Remote Sensing of Environment, First Thematic Conference: Remote sensing of arid and semi-arid lands*, 1982.

[9] W. Sun, B. Chen, and D. Messinger, “Nearest-neighbor diffusion-based pan-sharpening algorithm for spectral images,” *Opt. Eng.*, vol. 53, no. 1, 2014.

[10] R. A. Schowengerdt, “Reconstruction of multispatial, multispectral image data using spatial frequency content, *Photogramm Eng. Remote Sens.*, vol. 46, no. 10, pp. 1325-1334, 1980.

[11] H. Holland, *Adaptation in Natural and Artificial Systems*, Ann Arbor: The University of Michigan Press, 1975.

[12] M. Yu, “Image segmentation using genetic algorithm and morphological operations,” Master’s Thesis, Iowa State University, 1998.

[13] K. S. Tang, K .F. Man, S. Kwong, and Q. He, “Genetic algorithms and their applications,” *IEEE Signal Process. Mag*., vol. 13, no. 6, pp. 22-37, 1996.

[14] L. Wald, “Fusion of Images of Different Spatial Resolutions,” Presses de l'Ecole, Ecole des Mines de Paris France, 2002.

[15] Z. Wang and Q. Li, “Information content weighting for perceptual image quality assessment,” *IEEE Trans. Image Process.*, vol. 20, pp. 1185–1198, 2011.

[16] Z. Wang, and A. C. Bovik, “A universal image quality index,” *IEEE Signal Process. Lett.*, vol. 9, pp. 81–84, 2002.

[17] M. B. Haghighat, A. A. Aghagolzadeh, and H. Seyedarabi, “A Non-Reference Image Fusion Metric Based on Mutual Information of Image Features,” *Comput. Electr. Eng.*, vol. 37, no. 5, pp. 744-756, 2011.

[18] A. Liu, W. Lin, and M. Narwaria, “Image quality assessment based on gradient similarity,” *IEEE Trans. Image Process.*, vol. 21, pp. 1500–1512, 2012.