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A Rudin-Osher-Fatemi Model-Based Pansharpening Approach Using RKHS and AHF Representation

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Abstract. A pansharpening method based on the Rudin-Osher-Fatemi model and using a reproducing kernel Hilbert space along with the approximated Heaviside function is developed. The corresponding minimisation problem is solved by the alternating direction method of multipliers. Numerous numerical experiments with Pléiades and IKONOS satellite datasets demonstrate the efficiency of the method in preserving spectral and spatial information and show its superiority to other approaches.

AMS subject classifications: 47N10, 65C20, 68U10

Key words: Multi-spectral image, reproducing kernel Hilbert space, pansharpening, approximated Heaviside function.

1. Introduction

The remote sensing images acquired by earth resource satellites — e.g. by QuickBird, IKONOS, Landsat, are used to monitor the surface of the earth. They play an important role in military intelligence, environmental monitoring, land-cover classification and so on. Such images usually consist of two components — viz. the multi-spectral (MS) and panchromatic (PAN) images which, respectively, provide spectral and spatial information. At the same time, the high-resolution MS images are used in various applications, including pattern classification, land-cover management, environmental monitoring, weather forecasting, and topographic map updating [7]. Nevertheless, physical and technical limitations often lead to low resolution MS images. Therefore, the development of a super-resolution technique is needed. The super-resolution of an MS image consists in deriving an HRMS

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image in both spatial and spectral domains by blending the geometric details of PAN image and the rich spectral information of MS image. This fusion process is referred to as pansharpening.

The pansharpening has attracted intensive attention in remote sensing. According to Amro *et al.* [6], the pansharpening methods can be roughly classified into five categories — viz. Component Substitution (CS), Relative Spectral Contribution (RSC), High-Frequency Injection (HFI), Image Statistics Based (ISB), and Multiresolution Analysis (MRA). The CS methods carry out spectral transformation, do the upsampling of a low resolution multi-spectral (LRMS) images and substitute the corresponding components by high-resolution PAN images. Classical CS methods include the intensity-hue-saturation [11, 40], the principal component analysis [34] and the Gram-Schmidt (GS) spectral sharpening [30]. On the other hand, the RSC methods can be considered as an alternative to CS pansharpening methods, which works with linear combinations of spectral bands instead of substitutions. The HFI methods proposed by Schowengerdt [37], add the high-frequency content of the PAN image to upsampled LRMS images. The ISB methods use statistical information of LRMS and PAN images during the pansharpening — cf. [24]. The MRA approach decomposes low resolution multi-spectral and PAN images into different spatial levels and improves the spatial details of low resolution multi-spectral images by adding high frequencies from the PAN image. The corresponding approaches include Laplacian pyramid [10], à-trous wavelet transform [38] and additive wavelet luminance proportional method [33].

In addition to the already mentioned approaches, another possibility to improve MS images is provided by variational methods. The main idea of these methods consists in the construction of an energy functional, which utilises prior information and assumptions, and in finding the optimal solutions of the corresponding optimisation problem. In particular, Ballester *et al.* [8] introduced a variational pansharpening model named $P+XS$-method. It is based on the assumption that the geometry of the MS components are contained in the topographic map of the PAN image, which in turn is the linear combination of HRMS components. However, such interaction between PAN and MS images at the high spatial resolution produces spectral distortion [39]. Möller *et al.* [32] proposed a variational scheme with integrate wavelet fusion into the $P+XS$-method. Restaino *et al.* [35] applied mathematical morphology to pansharpening and demonstrated the efficiency of this approach for several data sets. Papers [7, 21] provide an extensive review of pansharpening methods. Jiang *et al.* [28] used a hyper-Laplacian based pansharpening model. It estimates the final pan-sharpened image directly, but not the coefficients of a basis as we do here. In addition, differential operators are applied to the difference of latent combined HRMS and panchromatic images, and a hyper-Laplacian regularisation is used. On the other hand, in order to simultaneously fuse panchromatic and multispectral images, Zhang *et al.* [47] presented a framelet based iterative pansharpening method. Unlike [28, 47], this model is based on a reproducing kernel Hilbert space and the Heaviside function, where the former keeps the main image data and the later deals with the image edges. The coefficients in the reproducing kernel Hilbert space and the Heaviside basis are used to foresee unknown pixels, thus increasing the image resolution. In addition, an iterative strategy to enhance the performance of image pansharpening is employed.