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Area-to-point regression kriging for pan-sharpening

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ABSTRACT

Pan-sharpening is a technique to combine the fine spatial resolution panchromatic (PAN) band with the coarse spatial resolution multispectral bands of the same satellite to create a fine spatial resolution multispectral image. In this paper, area-to-point regression kriging (ATPRK) is proposed for pan-sharpening. ATPRK considers the PAN band as the covariate. Moreover, ATPRK is extended with a local approach, called adaptive ATPRK (AATPRK), which fits a regression model using a local, non-stationary scheme such that the regression coefficients change across the image. The two geostatistical approaches, ATPRK and AATPRK, were compared to the 13 state-of-the-art pan-sharpening approaches summarized in Vivone et al. (2015) in experiments on three separate datasets. ATPRK and AATPRK produced more accurate pan-sharpened images than the 13 benchmark algorithms in all three experiments. Unlike the benchmark algorithms, the two geostatistical solutions precisely preserved the spectral properties of the original coarse data. Furthermore, ATPRK can be enhanced by a local scheme in AATRPK, in cases where the residuals from a global regression model are such that their spatial character varies locally.

1. Introduction

Satellite sensors such as WorldView, QuickBird, IKONOS, SPOT and Landsat ETM+ can acquire information about the same area on the Earth's surface at different spatial resolutions and in different wavebands. For example, the WorldView multispectral sensor can acquire images in eight bands with a spatial resolution of 2 m, while the WorldView panchromatic (PAN) sensor can acquire a single band image with a spatial resolution of 0.5 m. It is of great interest to fuse such fine spatial resolution PAN band images with coarse spatial resolution multispectral bands covering the same area to generate a fine spatial resolution multispectral image. Pan-sharpening is an image fusion technique developed for this purpose. By taking full advantage of images in different wavebands from the same satellite, pan-sharpened data are able to provide more detailed land-cover/land-use (LCLU) information than the original multispectral data.

Pan-sharpening has been a lively topic in the remote sensing community and has motivated considerable research over the past decades. Several reviews on pan-sharpening approaches exist (Vivone et al., 2015; Pohl and Van Genderen, 1998; Wang et al., 2005; Zhang and Mishra, 2014; Zhang, 2010). Vivone et al. (2015) reviewed some widely used pan-sharpening algorithms and categorized them into two main types, including component substitution (CS) and multiresolution analysis (MRA). The core idea of CS is to transform the original multispectral data into another space and substitute one of the components with the PAN band. Algorithms falling into this type include intensity-hue-saturation (IHS) (Tu et al., 2001; Zhou et al., 2014), Brovey transformation (Gillespie et al., 1987), principal component analysis (PCA) (Shettigara, 1992), Gram-Schmidt (GS) transformation (Laben and Brower, 2000), adaptive GS (GSA) (Aiazzi et al., 2007), and partial replacement adaptive component substitution (PRACS) (Choi et al., 2011). The MRA approach injects the spatial detail produced by multiresolution decomposition of the PAN band. Common MRA examples are high-pass filtering (HPF) (Chavez et al., 1991), smoothing filter-based intensity modulation (SFIM) (Liu, 2000), decimated wavelet transform using an additive injection model (Indusion) (Khan et al., 2008), *a trous* wavelet transform (ATWT) (Vivone et al., 2014), additive wavelet luminance proportional

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(AWLP) (Nunez et al., 1999), ATWT using the Model 2 (ATWT-M2) (Ranchin and Wald, 2000) and Model 3 (ATWT-M3) (Ranchin and Wald, 2000), generalized Laplacian pyramid (GLP) with modulation transfer function (MTF)-matched filter (MTF-GLP) (Aiazzi et al., 2006), and GLP with MTF-matched filter and multiplicative injection model (MTF-GLP-HPM) (Lee and Lee, 2010). In addition, sparse representation-based pan-sharpening approaches have also received increasing attentions (Cheng et al., 2015).

Geostatistical solutions provide another family of approaches for pan-sharpening. They have the significant advantage of preserving the spectral properties of the observed coarse images: that is, when upscaling the pan-sharpened image to the original coarse spatial resolution, the result is identical to the original one, a property referred to as perfect coherence. Pardo-Igúzquiza et al. (2006) sharpened Landsat ETM+ images with downscaling cokriging (DSCK), which treats each observed coarse band as the primary variable and the PAN band as the secondary variable. DSCK was extended with a spatially adaptive filtering scheme (Pardo-Igúzquiza et al., 2006), in which the cokriging weights change across the whole image. Tang et al. (2015) considered multiple-point statistics as a post-processing step of DSCK to increase the accuracy of pan-sharpening. Atkinson et al. (2008) extended the DSCK approach to increase the spatial resolution of the multispectral bands beyond that of any input images including the PAN band. However, the one-stage DSCK approach requires complex auto-semivariogram and cross-semivariogram modeling for each coarse band, which makes it difficult to automate (Sales et al., 2013).

Similarly to the issue defined for pan-sharpening, some other geostatistical solutions were developed for fusing MODIS bands 1–2 and bands 3–7. Specifically, Sales et al. (2013) proposed a kriging with external drift (KED) approach. KED requires only auto-semivariogram modeling for the observed coarse band and is easier to implement than DSCK (Sales et al., 2013). KED, however, suffers from expensive computational cost, as it computes kriging weights locally for each fine pixel (Sales et al., 2013). The computing time is related directly with the number of fine pixels to be predicted. In view of this, in previous work (Wang et al., 2015), we proposed an area-to-point regression kriging (ATPRK) approach for MODIS image downscaling. ATPRK is faster than KED and more user-friendly than DSCK. Moreover, ATPRK can incorporate readily other additional data for possible enhancement.

The objective of fusing MODIS bands 1–2 and bands 3–7 is physically different from that for pan-sharpening other data (e.g., very high resolution (VHR) images). First, MODIS bands 1–2 and bands 3–7 are not acquired in the same spectral range, while the PAN and corresponding multispectral bands of the satellite sensor are almost in the same spectral range. Thus, the PAN band can, theoretically, provide more relevant fine spatial resolution information for sharpening. Second, due to the differences in spatial resolution, the spatial content in MODIS data is generally different from that in Landsat and VHR images. The 500 m MODIS images are commonly used for global monitoring of large scale LCLU information, such as in relation to vegetation, water and snow cover. The 2–4 m VHR images are used generally for local detection or monitoring of small-sized LCLU objects of interest, including impervious surfaces, urban objects, and military targets (such as planes and ships).

In this paper, based on encouraging performance in relation to MODIS image fusion (Wang et al., 2015) and its theoretical advantages, ATPRK is proposed for pan-sharpening. ATPRK models the overall trend in the target variables (i.e., fine spatial resolution pixels to be predicted) by regression of the primary variables (i.e., coarse spatial resolution bands to be downscaled) on a covariate (i.e., the PAN band degraded to coarse spatial resolution) (Hengl et al., 2004, 2007). Area-to-point kriging (ATPK) (Kyriakidis and Yoo, 2005; Kyriakidis, 2004; Atkinson, 2013) is then performed as the second step to downscale the coarse residuals from the regression process, the output of which are finally added back to the regression predictions to produce pan-sharpened images.

In Wang et al. (2015), the regression model was built using the global image (i.e., all pixels in the coarse band and the PAN band) and the regression coefficients were fixed for each coarse pixel. However, the spatial structure of LCLU sometimes demands a non-stationary model, that is, with parameters that vary spatially (Wang et al., 2014). For example, in the studied image, some large regions may be dominated by impervious surfaces in urban areas, while some other large regions may be mainly covered by vegetation. The obvious difference in spectra of the LCLU classes will lead to the requirement for non-stationary parameters and, thus, the relationship between the coarse band and the PAN band may not be sufficiently characterized by a single, global regression model. To this end, a secondary objective of this paper was to extend the recently developed ATPRK with a spatially adaptive scheme, called adaptive ATPRK (AATPRK). AATPRK characterizes the relationship between each coarse band and the PAN band using the local spatial structure and a regression model fitted on a per-coarse pixel basis.

The contributions of this paper are, thus, threefold.

(1) A new geostatistical approach, ATPRK, is applied for pan-sharpening VHR images for the first time. The problem of pan-sharpening VHR images is an important one, is commonly encountered in remote sensing, and is different from the fusion of medium spatial resolution images (e.g., MODIS images), as mentioned above.
(2) A systematic comparison between ATPRK and the state-of-the-art approaches to pan-sharpening, as introduced above.
(3) Extension of ATPRK with the proposed non-stationary spatially adaptive scheme, that is, AATPRK.

The remainder of this paper is organized into four sections. Section 2 introduces the principles of ATPRK and AATPRK in detail. In Section 3, the experimental results for two WorldView-2 datasets and one Landsat ETM+ dataset are provided to demonstrate the applicability of ATPRK and AATPRK in pan-sharpening. Section 4 further discusses the proposed approach, followed by a conclusion in Section 5.

2. Methods

Let $Z_C^l(\mathbf{x}_i)$ be the measurements (i.e., gray value) of pixel C centered at $\mathbf{x}_i$ ($i = 1, \ldots, M$, where M is the number of pixels) in coarse band l ($l = 1, \ldots, B$, where B is the number of bands), and $Z_F(\mathbf{x}_j)$ be the measurements of pixel F centered at $\mathbf{x}_j (j = 1, \ldots, MG^2$, where G is the spatial resolution (zoom) ratio between the coarse and PAN bands) in the PAN band. The notations F and C denote the fine and coarse pixels, respectively. The objective of pan-sharpening is to predict target variables $Z_F^l(\mathbf{x})$ for all fine pixels in all B coarse bands.

2.1. ATPRK

ATPRK contains two steps: regression modeling and ATPK-based residual downscaling. Suppose $\hat{Z}_{F1}^l(\mathbf{x})$ and $\hat{Z}_{F2}^l(\mathbf{x})$ are predictions of the regression and ATPK parts, the ATPRK prediction is

$$\hat{Z}_F^l(\mathbf{x}) = \hat{Z}_{F1}^l(\mathbf{x}) + \hat{Z}_{F2}^l(\mathbf{x}). \quad (1)$$

Details of the calculation processes are given in the following.