remote sensing

Editorial

Editorial to Special Issue "Multispectral Image Acquisition, Processing, and Analysis"

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1. Overview of the Issue: Multispectral Image Acquisition, Processing, and Analysis

This Special Issue was announced in March 2018. The ideas and motivations behind this issue were the following. First, there is a high interest in the corresponding systems and technologies. Really, due to continually improving advances in lightweight and less expensive versions of multispectral sensors and remote sensing platform technology in recent years, end-users are provided with a multitude of timely observational capabilities for better sensing and monitoring of the Earth surface. To benefit from the full potential of these ever-advancing productive systems in a more flexible and smart way in many applied fields, researchers and system developers have to continue improving analysis methods and processing capabilities. Joint efforts for fully automated, easy-to-use, and efficient systems are a key goal for the facilitation and maturation of the operational use of remote sensing. Second, there is a wide diversity of questions that could be considered within the scope of the Special Issue, namely:

(1) State-of-the-art and emerging multispectral technologies, including new platforms (satellite, aerial, Unmanned Aerial Vehicles) and sensors with: spatial, spectral, and temporal sensing abilities; georeferencing and navigation abilities; cooperative sensing.
(2) Advanced multispectral image/data analysis and processing: lossless/lossy compression, and denoising; geometrical, registration, and georeferencing processing; feature extraction, classification, object recognition, change detection, and domain adaptation.
(3) Multisource data fusion: optical-radar fusion and pan-sharpening; field sensing; crowd sensing.

A wide spectrum of the recent and latest emerging applications were also considered, including: multispectral image acquisition, processing, and analysis targeted on biodiversity assessment; vegetation and environmental monitoring (identification of diversity in grassland species, invasive plants, biomass estimation, and wetlands); precision agriculture in agricultural ecosystems and crop management; water resource and quality management in nearshore coastal (mapping near-surface water constituents, benthic habitats) and inland waters (analysis and surveying of rivers and lakes); sustainable forestry and agroforestry (forest preservation and mapping of forest species, wildfire detection); mapping archaeological areas, urban development, and management; and hazard monitoring.

As a result of our work as guest editors, 20 submissions have been received, from which nine have been rejected. The accepted publications can be conditionally divided into three groups dealing with (a) data pre-processing methods; (b) image fusion and classification; and (c) object detection and extraction of specific information from remote sensing data.

The first group contains four papers. One of them, "Spectral Super-Resolution with Optimized Bands" by U.B. Gewali, S.T. Monteiro, and E. Saber, considered hyperspectral (HS) reflectance spectrum reconstruction from multispectral (MS) data [1]. The peculiarity of the proposed method was that joint optimization of the used MS bands and the transformation from MS signal to HS spectra were carried out. A neural network architecture for optimizing MS bands was presented, and an approach to its learning was given. This super-resolution network with a new loss function produced high fidelity HS spectra reconstruction. Advantages of the proposed approach were demonstrated for the task of land cover classification.

The paper "A Local Feature Descriptor Based on Oriented Structure Maps with Guided Filtering for Multispectral Remote Sensing Image Matching" by T. Ma, J. Ma, and K. Yu considered the task of multispectral image matching in conditions of significant nonlinear intensity variations [2]. The authors designed a new local feature descriptor and a novel guidance image extractor able to detect highly similar structure information in multispectral data. The advantage the proposed descriptor was its robustness to intensity variations; this was proven by experiments performed for three commonly used datasets named Potsdam, EPFL, and CVC.

The paper "Pansharpening Using Guided Filtering to Improve the Spatial Clarity of VHR Satellite Imagery" prepared by J. Choi, H. Park, and D. Seo addressed an important task of improving the spatial clarity of very high resolution (VHR) satellite imagery [3]. In the proposed approach, guided filtering was employed to generate optimal multispectral images for pansharpening. In this sense, the approach differed from known ones that use guided filtering to extract spatial details. The proposed method and algorithms were successfully tested for KOMPSAT-3A data.

In the paper "Enhancement of Component Images of Multispectral Data by Denoising with Reference" by S. Abramov, M. Uss, V. Lukin, B. Vozel, K. Chehdi, and K. Egiazarian, it was shown that there are sub-band images that are quite noisy, and that it was worth carrying out filtering for them [4]. For this purpose, component images with high input signal-to-noise ratio could be used as a reference under the condition of proper pre-processing. The use of joint filtering of noisy and reference images leads to a sufficient improvement of the quality of noisy images. This was shown for Sentinel multispectral data.

The second group of papers focused on information extraction. It is also composed of four contributions. The first one was oriented towards the fusion of the panchromatic and low spatial-resolution multispectral images for generating high spatial-resolution multispectral images. It is entitled "Fusion of Multispectral and Panchromatic Images via Spatial Weighted Neighbor Embedding" by K. Zhang, F. Zhang, and S. Yang [5]. A spatial weighted neighbor embedding (SWNE) approach is suggested. The neighbors and the associated reconstruction weights were estimated by a resolution based on the alternative direction multiplier method (ADMM) optimization of an appropriate weighted problem to exclude some outliers. The proposed approach was proven to be more effective than other methods in terms of spatial enhancement and spectral preservation on QuickBird and Geoeye-1 satellite image datasets.

The second paper "Hyperspectral Image Classification with Multi-Scale Feature Extraction" by B. Tu, N. Li, L. Fang, D. He, and P. Ghamisi investigated the classification of hyperspectral images by means of a Gaussian pyramid based multi-scale feature extraction (MSFE) [6]. Spatial texture features of different scales were thereby captured. Then, support vector machine (SVM) based probability maps in each layer of the Gaussian pyramid were optimized through edge-preserving filtering (EPF). The majority voting method was considered for determining the label of pixels, thus producing the final classification map. Better accuracy over other classification methods, especially with a quite limited number of training samples, was demonstrated on Indian Pines and Salinas AVIRIS datasets and the University of Pavia Reflective Optics System Imaging Spectrometer (ROSIS) dataset.

The penultimate manuscript "A Multiscale Hierarchical Model for Sparse Hyperspectral Unmixing" by J. Zou and J. Lan covered unsupervised multi-scale hierarchical sparsity unmixing [7]. The large scale spatially regularized unmixing problem was broken into two different problems in different image domains. One approximation domain was obtained by using multi-scale spatial resampling, and thus captured coarse spatial contextual information and the original domain represented fine-scale details. In the coarse domain, multilayer sparsity based on L1/2 norm was considered to cope with spectral variability and achieve more accurate endmembers and abundance matrix. Then, the abundance matrix was converted back to the original domain and used to regularize the unmixing process so as to promote the spatial dependency between neighboring pixels. The proposed method was shown to outperform previous methods in endmember extraction and abundance fraction estimation with a reduced computational complexity—both on simulation datasets derived from the USGS digital library and real hyperspectral data experiments (Resonon Pika XC2 push broom imager ground-based dataset and HYDICE Urban dataset).

The last one, "FCM Approach of Similarity and Dissimilarity Measures with α-Cut for Handling Mixed Pixels" by S. Mukhopadhaya, A. Kumar, and A. Stein concerned the comparative accuracy assessment of alpha-cut embedding into fuzzy c-means classification with using different similarity and dissimilarity measures [8]. The goal was to highlight the two best measures and parameters whose combination and optimization allowed for better results to be obtained to handle the problem of mixed pixels as well as the effect of noise on the considered datasets. The comparative analysis was performed on images with different resolution and large heterogeneous areas with high complexity in the land cover (Landsat-8 and Formosat-2 images).

The third group is composed of three contributions related to object detection and feature extraction. The first one "Diffuse Skylight as a Surrogate for Shadow Detection in High-Resolution Imagery Acquired Under Clear Sky Conditions" by M. Cameron and L. Kumar proposed a solution for shadow detection in high spatial resolution images acquired under clear sky conditions from airborne/spaceborne sensors [9]. The method does not require complex sun-object-sensor corrections, and it is invariant to the exponential increase in scene complexity associated with higher-resolution imagery. It uses mainly Rayleigh scattering principles to create a diffuse skylight vector as a shadow reference. The method was evaluated on Worldview-3 and ADS40 images captured over a common scene.

The second one, "A Cloud Detection Method for Landsat 8 Images Based on PCANet" by Y. Zi et al. proposed a cloud detection method for Landsat 8 images based on several processing steps [10]. In a first step, the color composite images of Bands 6, 3, and 2 were divided into superpixel sub-regions through the Simple Linear Iterative Cluster (SLIC) method. Then, a two-step superpixel classification strategy was used to predict each superpixel as cloud or non-cloud. The bright and thick cloud superpixels, as well as the obvious non-cloud superpixels, are separated from potential cloud superpixels through a threshold function. Then high-level information is extracted using double-branch PCA Network (PCANet) combined with a Support Vector Machine (SVM) classifier. In the last step, a fully connected Conditional Random Field (CRF) model was used to refine the cloud detection results. The method was validated on the Landsat 8 Cloud Cover Assessment (L8 CCA) dataset.

The last contribution, "Thermal Airborne Optical Sectioning" by I. Kumi et al. proposes a multispectral (RGB and thermal) camera drone for synthetic aperture imaging [11]. The aim of this study was to remove the occluding vegetation to reveal hidden objects in applications related to archeology, search-and-rescue, animal inspection, and border control. The radiated heat signal of strongly occluded targets, such as human bodies hidden in dense shrub, could be made visible by integrating multiple thermal recordings from slightly different perspectives while being entirely invisible in RGB recordings or unidentifiable in single thermal images. In the experiments, they collected bits of heat radiation through the occluder volume over a wide synthetic aperture range and computationally combined them to a clear image. To estimate the drone's position and orientation for each capturing pose, computer vision algorithms were adopted.

2. Conclusions

From the eleven papers published in this special issue, we observe that the remote sensing community is still actively engaged in the development of advanced techniques to meet end-users' expectations. Building off these new advances and improvements, there will be increasing facilitation and maturation of remote sensing for operational use. We hope that the readers will enjoy this special issue.

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