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Trainable spectral difference learning with spatial starting for hyperspectral image denoising

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ABSTRACT

Because of the limited reflected energy and incoming illumination in an individual band, the reflected energy captured by a hyperspectral sensor might be low and there is inevitable noise that significantly decreases the performance of the subsequent analysis. Denoising is therefore of first importance in hyperspectral image (HSI) analysis and interpretation. However, most HSI denoising methods remove noise with the important spectral information being severely distorted. This paper presents an HSI denoising method using trainable spectral difference learning with spatial initialization (called HDnTSDL) aimed at preserving the spectral information. In the proposed HDnTSDL model, a key band is automatically selected and denoised. The denoised key band acts as a starting point to reconstruct the rest of the non-key bands. Meanwhile, a deep convolutional neural network (CNN) with trainable non-linearity functions is proposed to learn the spectral difference mapping. Then, the rest of the non-key bands are denoised under the guidance of the learned spectral difference with the key band as a starting point. Experiments have been conducted on five databases with both indoor and outdoor scenes. Comparative analyses validate that the proposed method: (i) presents superior performance in spatial recovery and spectral preservation, and (ii) requires less computational time than state-of-the-art methods.

1. Introduction

Hyperspectral image (HSI) describes the spectrum reflected by different materials in a scene with contiguous and narrow spectral bands (Du et al., 2013). The availability of this detailed spectral information has made HSI useful for a wide array of applications, such as military anomaly detection (Du & Zhang, 2014; Taghipour & Ghassemian, 2017; Tan et al., 2016), geological exploration (Asadzadeh & Roberto, 2016), and precision agriculture (Benediktsson, Palmason, & Sveinsson, 2005; Sharma, Liu, Yang, & Shi, 2017; Wang & Gao, 2015). However, the high spectral resolution implies the narrow slicing of the spectra in HSIs. In other words, a small amount of the reflected energy can reach the hyperspectral sensor in each band. Thus, the reflected energy captured by each sensor might be low, and there is inevitable noise because of the limited reflected energy and incoming illumination in individual band, which significantly decreases the performance of the subsequent analysis (Fu, Lam, Sato, & Sato, 2017). It is therefore important to denoise before HSI analysis and interpretation.

Many works have already highlighted two primary aspects for combining spatial and spectral features to improve performance: preprocessing modules and post processing modules (Asadzadeh & Roberto, 2016; Du et al., 2013). The HSI denoising process is of first importance in the field of HSI analysis and belongs to the pre-processing module, which aims at removing noise in both the spatial and spectral domains.

Although deep learning has been studied in various areas of computer vision for decades, an efficient model suited for HSI denoising remains an open problem. In this paper, we propose a novel HSI denoising method using trainable spectral difference learning with spatial starting to achieve good performance and require less computational time. Here, a deep convolutional neural network (CNN) with a trainable non-linearity function is designed to learn a spectral difference mapping between the noisy HSIs and the clean HSIs, which provides an accurate spectral reference for the denoising process. We use a real remote sensing HSI as an example to explain why we consider the CNN. As shown in Fig. 1, we can observe that certain unwanted components, such as shot noise, exist in the original bands of the real remote sensing HSIs. A simple convolution operation can remove noise to a certain degree as shown in the corresponding convolved bands.

Unlike existing CNN models where the thresholding function max (0, x), also known as rectified linear units (ReLU) (Du et al., 2017), is used, we propose a novel CNN with trainable non-linearity functions that learns the spectral difference mapping.

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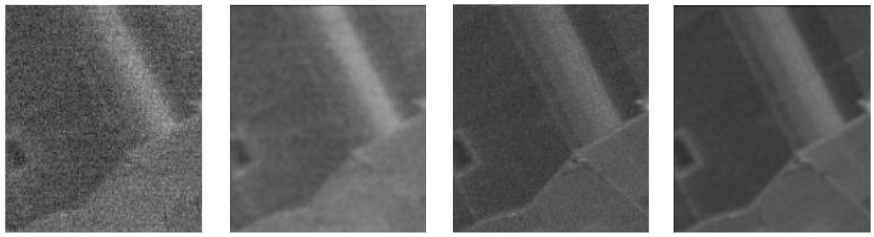

Fig. 1. Example of two original bands and the corresponding convoluted results in an HSI. Note that a simple convolution operation is used.

Currently, the automatic training of both the convolution parameters and the non-linearity functions in a CNN using a loss based method is a novel approach. Chen and Pock (2017) proposed a novel trainable nonlinear reaction diffusion (TNRD) model that simultaneously learned all of the parameters of the convolution operation and the non-linearity function from training data and successfully applied it to gray-scale image denoising. To the best of the authors' knowledge, this idea has not been exploited in the field of HSI denoising. Our work advances this knowledge, and we found that the spectral difference mapping is more suitable for HSI analysis. In addition, we introduce a feature extraction procedure to select a key band to be denoised. The denoised key band acts as a precise starting point to reconstruct the remaining non-key bands under the guidance of the learned spectral difference. This process is called spatial initialization. In essence, the spatial initialization is designed to constrain the spectral reconstruction process with a precise starting point. Our HSI denoising method using trainable spectral difference learning with spatial initialization (called HDnTSDL) achieves HSIs denoising while preserving the spectral information.

In summary, we make three contributions: (1) We propose HDnTSDL, a novel HSI denoising scheme based on spectral difference learning with spatial initialization. It is robust to denoise and preserve spectra. (2) We introduce a novel CNN with the trainable non-linearity functions, which is unlike the conventional CNN with the specific non-linearity functions, and successfully apply it to analyze HSI. (3) We propose a band selection algorithm based on feature extraction that is more suitable for HSIs with regard to physics significance, which avoids spectral distortion. Especially, unlike existing methods, where the CNN model is mainly used to extract spatial features, we explored the performance of the CNN model to characterize the spectral correlation. Experiments have been conducted on HSIs from five different databases that include both indoor and outdoor scenes. Comparative analyses have validated the effectiveness and efficiency of our proposed HDnTSDL method by achieving state-of-the-art performance while running much faster than other competing methods.

The remainder of this paper is divided into five sections. Section 2 reviews the related works about HSI denoising methods and deep learning used in HSI applications. In Section 3, we describe the flowchart of the proposed methodology. Section 4 is devoted to the experimental results. In the last section, a conclusion is made.

2. Related work

2.1. HSI denoising method

HSI denoising methods presently can be classified into three categories: 2D extended methods (Buades, Coll, & Morel, 2005; Maggioni & Foi, 2012; Mairal, Elad, & Sapiro, 2008), tensor based methods (Maggioni, Katkovnik, Egiazarian, & Foi, 2013; Peng et al., 2014; Xie et al., 2016) and partial differential equation (PDE) based methods (Mndez-Rial & Martn-Herrero, 2012; Wu, Wang, Jin, & Shen, 2017; Zhao & Yang, 2015). The simplest way is to extend the classical 2D denoising methods to HSI band by band, such as the block-matching and 3D filtering (BM3D) (Maggioni & Foi, 2012), the non-local means (NLM) (Buades et al., 2005) and K-singular value decomposition (K-SVD) (Mairal et al., 2008). However, the corresponding results of this extension cannot achieve good performance because HSI denoising band by band neglects the primary component, spectra, which may distort spectral information. The second group is based on the tensor decomposition method in which an HSI is regarded as a tensor. These methods include parallel factor analysis (PARAFAC), tensor dictionary learning (TDL) (Peng et al., 2014) and intrinsic tensor sparsity (ITS) (Xie et al., 2016). Among these methods, BM4D (Maggioni et al., 2013) and ITS offer state-of-art performance for many HSI databases. These tensor decomposition based methods jointly take into account the spectral–spatial information and effectively preserve the original spectral information. However, a problem is that the application of a core tensor and tensor product can lead to information compression and the loss of spatial details. In addition, the tensor decomposition based method is time consuming. The PDE based methods are another powerful tool for HSI denoising, such as total variation (Wu et al., 2017), anisotropic diffusion model (Mndez-Rial & Martn-Herrero, 2012) and low rank models (Zhao & Yang, 2015). Note that the PDE based method is always handcrafted and it is difficult to design a proper PDE for HSI denoising. Moreover, all these methods denoised the HSI without specifically preserving the important spectral information. To handle the obstacles of spatial quality deterioration and noisy spectra, we simultaneously exploited the spatial and spectral correlations. Our method fundamentally differs from existing HSI denoising methods in that ours explicitly learns the spectral difference to reconstruct the clear band.

2.2. Deep learning for HSI restoration

CNN has the advantage of local connections and shared weights that can reduce computational cost. This method has recently had an explosion in popularity due to its success in HSI processing applications, such as classification (Makantasis, Karantzalos, Doulamis, & Doulamis, 2015; Tuia, Flamary, & Courty, 2015; Zhao & Du, 2016a), dimensionality reduction (Zhao & Du, 2016b), feature extraction (Chen, Jiang, Li, Jia, & Ghamisi, 2016; Li, Xie, & Li, 2017), and fusion (Chen, Li, Ghamisi, Jia, & Gu, 2017; Mei, Ji, Hou, Li, & Du, 2017; Palsson, Sveinsson, & Ulfarsson, 2017). Yuan, Zheng, and Lu (2017) directly applied the CNN model proposed by Dong, Loy, He, and Tang (2016) to super-resolve HSIs, but this method did not consider spectral information preservation and the difference between HSIs and RGB images. Currently, few works have used the CNN to remove noise in HSIs. Xie and Li (2017) proposed a deep learning model with trainable non-linearity functions for HSI denoising, but the spectral information cannot be preserved well. By far, it remains a challenge to develop CNN for HSI denoising.