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Impulse denoising for hyper-spectral images: A blind compressed sensing approach

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ABSTRACT

In this work we propose a technique to remove sparse impulse noise from hyperspectral images. Our algorithm accounts for the spatial redundancy and spectral correlation of such images. The proposed method is based on the recently introduced Blind Compressed Sensing (BCS) framework, i.e. it empirically learns the spatial and spectral sparsifying dictionaries while denoising the images. The BCS framework differs from existing CS techniques that employ fixed sparsifying basis; BCS also differs from prior dictionary learning studies which learn the dictionary in an offline training phase. Our proposed formulation has shown over 5 dB improvement in PSNR over other techniques.

1. Introduction

In this work, we address the problem of denoising hyper-spectral images when they are corrupted by impulse noise. Previously, most studies in hyper-spectral denoising only concentrated on removing Gaussian noise. However, hyper-spectral images are also corrupted by impulse noise [1–3]; there is hardly any work on impulse denoising for hyper-spectral images. The impulse noise arises when some of the sensors become saturated (leading to ones) or when they do not work (leading to zero valued pixels). The problem of impulse denoising in hyperspectral imaging is relatively new; hence there are not many prior studies on this topic.

There have been studies in removing impulse noise from gray-scale (single band) images. There are two approaches to address single band impulse denoising – traditional median filter based methods [4,5] and modern optimization based techniques [6–8]. The optimization based techniques are more flexible in handling random valued impulse noise, while the median filtering variants are mostly suited for extreme valued salt-and-pepper noise.

Techniques developed for removing impulse noise from grayscale images can be applied on each spectral bands of the hyperspectraldatacube, but such an approach would not be optimal. This is because, the hyperspectral images are spectrally correlated, and such piecemeal (band-by-band) denoising techniques do not account for the spectral correlation. Prior studies in Gaussian noise removal from hyperspectral images showed that exploiting the spectral correlation indeed improves denoising results [9–11].

For denoising, the transform domain sparsity of the signal is usually exploited. Previously, data independent transforms (like wavelets) were used to sparsify the image; but in recent times it was observed that data dependent learned dictionaries yield better results for both Gaussian [12], impulse [7,8] and even speckle [13] denoising.

In this work, we propose to exploit the spatio-spectral redundancy of the hyper-spectral datacube to reduce impulse noise. Such a problem has not been addressed before. However, instead of employing a fixed dictionary, we will learn the dictionary while denoising the hyperspectraldatacube. Our

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approach is based on the Blind Compressed Sensing (BCS) approach [14]. Unlike prior studies [7,8,12,13], we do not learn the dictionary in an offline stage and then use the learned dictionary for denoising; rather we learn the dictionary while denoising in an online fashion. This is the fundamental difference between BCS and prior dictionary learning techniques – BCS marries dictionary learning with signal estimation.

The rest of the paper will be organized into several sections. Relevant studies will be briefly reviewed in Section 2. Our proposed approach will be described in Section 3. The experimental results will be shown in Section 4. The conclusions of this work and future direction of research will be discussed in Section 5.

2. Review of literature

We are interested in the additive noise model; both Gaussian noise and impulse noise belong to this category. The noise model can be expressed as follows:

$$y = x + \eta \tag{1}$$

where x is the original image (to be estimated) corrupted to by noise η to yield a noisy image y.

Sparsity based techniques assume that the image is sparse in a transform domain such as wavelets. Incorporating wavelet domain sparsity in (1) leads to:

$$y = W^T \alpha + \eta \tag{2}$$

where α is the sparse wavelet coefficients, W is the wavelet transform (W^T is the inverse).

Gaussian denoising is the most well studied problem; assuming that the noise is zero mean with unit variance, denoising is achieved by solving for the sparse wavelet coefficients:

$$\min_{\alpha} \|y - W^T \alpha\|_2^2 + \lambda \|\alpha\|_1 \tag{3}$$

The l_2-norm data fidelity term arises owing to the nature of Gaussian noise; the l_1-norm regularization promotes a sparse solution. Wavelet sparsity is very well known topic in Gaussian denoising and does not require any reference for support.

There are also Total Variation (TV) [15] based denoising techniques that express denoising in the analysis form, i.e.

$$\min_{x} \|y - x\|_2^2 + \lambda \mathrm{TV}(x) \tag{4}$$

TV assumes that images are piecewise smooth; with finite number of jump discontinuities. This leads to a sparse representation in finite difference.

Gaussian noise is dense but usually small in magnitude – it corrupts all the pixel values but the magnitude of corruption is small. In such a case, an l_2-norm data fidelity is an ideal choice. Impulse noise is sparse but has larger amplitudes. An extreme case of impulse noise is the salt-and-pepper noise where the pixels are corrupted to either the maximum or minimum possible values; there can also be random valued impulse noise. In either case, as the number of corrupted pixels is small, an l_1-norm data fidelity is more appropriate [6,16]

$$\min_{x} \|y - x\|_1 + \lambda \mathrm{TV}(x) \tag{5}$$

One can also formulate impulse denoising in the synthesis form, by exploiting wavelet domain sparsity instead of TV.

So far we have discussed techniques that exploit the sparsity of the image in a known basis (wavelet or finite difference). A seminal work [12] showed that it is possible to improve upon these results by learning the sparsifying dictionary. In dictionary learning, the dictionary is first learnt from image patches, such that the learnt dictionary can represent the patches in a sparse fashion. The learning problem is expressed as

$$\min_{D,Z} \|W - DZ\|_2^2 \text{ such that } Z \text{ is sparse} \tag{6}$$

here W is the training set of image patches, D is the learnt dictionary and Z is the sparse representation of the patches in dictionary D.

The learnt dictionary is later used for image denoising in the same manner as a wavelet dictionary, i.e. it is assumed that $x = Dz$. The denoising is expressed as

$$\min_{z} \|y - Dz\|_2^2 + \lambda \|z\|_1 \tag{7}$$

Recent studies in impulse denoising [7,8] adopted the same technique. Since the interest is in impulse noise, the data fidelity term is an l_1-norm instead of an l_2-norm

$$\min_{z} \|y - Dz\|_1 + \lambda \|z\|_1 \tag{8}$$

So far, we have talked about denoising gray scale (single spectral band) images. In hyperspectral imaging, the image is acquired at multiple spectral bands. The images at different bands are correlated to one another. To reduce noise from such images, it is possible to apply the techniques developed for single band images to each of the spectral bands separately. But this does not yield the best possible results. Such techniques only exploit the spatial redundancies within each band; better results can be obtained by jointly exploiting the spatial and spectral correlations.

The noise model for hyperspectral images is as follows:

$$Y = X + N \tag{9}$$

Each column of X represents a clean hyperspectral image from a band; the columns of Y are the noisy versions of these images. The problem is to recover X given the noisy images Y.

It is well known that 2D wavelets lead to a sparse representation of images; this concept was extended to the hyperspectraldatacube – in [17] it was shown that the datacube is sparse in 3D wavelets and hence denoising can be formulated as

$$\min_{\alpha} \|\mathrm{vec}(Y) - W_{3D}^T \alpha\|_2^2 + \lambda \|\alpha\|_1 \tag{10}$$

here $\alpha = W_{3D}\mathrm{vec}(X)$.

Similarly, there are other works that exploit the TV framework for denoising hyperspectral images using spatio-spectral correlations [10]. In some other studies [9], it is additionally assumed that the datacube X is of low-rank, this is because the columns of X are not linearly independent owing to spectral correlations.