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Application of Least Square Denoising to improve ADMM based Hyperspectral Image Classification

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Abstract

Hyperspectral images contain a huge amount of spatial and spectral information so that, almost any type of Earth feature can be discriminated from any other feature. But, for this classification to be possible, it is to be ensured that there is as less noise as possible in the captured data. Unfortunately, noise is unavoidable in nature and most hyperspectral images need denoising before they can be processed for classification work. In this paper, we are presenting a new approach for denoising hyperspectral images based on Least Square Regularization. Then, the hyperspectral data is classified using Basis Pursuit classifier, a constrained L1 minimization problem. To improve the time requirement for classification, Alternating Direction Method of Multipliers (ADMM) solver is used instead of CVX (convex optimization) solver. The method proposed is compared with other existing denoising methods such as Legendre-Fenchel (LF), Wavelet thresholding and Total Variation (TV) . It is observed that the proposed Least Square (LS) denoising method improves classification accuracy much better than other existing denoising techniques . Even with fewer training sets, the proposed denoising technique yields better classification accuracy, thus proving least square denoising to be a powerful denoising technique.

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Keywords: Denoising; hyperspectral image classification; basis pursuit; ADMM algorithm; Least Square; Legendre-Fenchel transformation.

1. Introduction

A new trend in remote sensing field is the Hyperspectral Imagery (HSI), which differs from other imaging systems in the sense that the number of bands captured by the imaging sensor is 100 to 200 or even greater. In a hyperspectral image, contiguous or non-contiguous bands of around 10nm bandwidth are available within the range of 400-2500 nm in the electromagnetic spectrum. The presence of a huge number of bands in a hyperspectral data makes it a hub of information resource, which can be used to classify features from captured image with more precision and detail. They can be used to precisely differentiate between land cover types and also to detect minerals, perform precision farming

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and urban planning, etc.[1] In recent years, many algorithms are being developed for many hyperspectral applications namely, image classification, unmixing of bands, target detection, sub-pixel mapping, pansharpening, etc.

Classification of objects using HSI data is not contextual, where contextual means focusing on the relationship between nearby pixels. Normal image classification is performed by grouping pixels to represent land cover features such as urban, forest, agriculture, etc. But in HSI classification, each pixel vector is classified into different categories. Pixel vectors with similar characteristics are classified into the same group. A number of new classifiers are being developed and experimented on HSI data. Important classifiers used till date are Support Vector Machines (SVM)[2], Polynomial based Multinomial Logistic Regression (MLR), Minimum Spanning Forest (MSF), Orthogonal Matching Pursuit[3], etc. Some of the classifiers are sparsity-based, including the one we have employed in this work. Basis pursuit (BP), which is used here for classification, decomposes a signal to an optimal superposition of dictionary elements. The optimization criterion of BP is L1-norm of coefficients. It is superior in terms of stability and super-resolution over many other methods like Best Ortho Basis, Matching Pursuit and more[4]. The L1-norm problem is solved by using ADMM (Alternating Direction Method of Multipliers). It has been shown that ADMM is much faster than other solvers like CVX (convex optimization)[2].

But, the accuracy of classification is reduced by the presence of noise in the images. So, hyperspectral images need to be pre-processed before they are classified. Here, a new denoising technique is put forward based on Least Square (LS) Regularization which effectively denoises the HSI data and improves classification accuracy. Also, the proposed LS denoising is much faster than other denoising methods, thus reducing pre-processing time requirement. LS based denoising is compared with other denoising techniques such as Legendre-Fenchel (LF)[2], Wavelet based denoising and Total Variation (TV) denoising techniques. Standard hyperspectral datasets such as Indian pines, Pavia University and Salinas Scene[1,2,3] are used for experimental purposes. This paper explains the application of LS denoising to hyperspectral images in section 2, classification of hyperspectral images in section 3, and section 4 discusses the experimental results and analysis.

2. Least Square based Hyperspectral Image denoising

The objective of denoising is to obtain a clean signal x from a given noisy signal y. Each pixel may be represented by x_{ijb} for signal x and y_{ijb} for signal y. The indices i, j and b are the row position, column position and the band number respectively for the signals x and y. Assuming that the noise is additive zero-mean Gaussian, we can represent denoised signal y as

$$y_{ijb} = x_{ijb} + w_b \tag{1}$$

where, w_b is the noise component with a standard deviation of σ and is band-dependent. Solution to this problem is not unique as it is a problem of estimating $\hat{x}$ from y, which has an L2 fidelity term, $\hat{x} = argmin_x \|y - x\|_2^2$. This term is extended for denoising approach as a Least Square problem, which is formulated as

$$\min_x \|y - x\|_2^2 + \lambda \, \|\mathbf{D}x\|_2^2 \tag{2}$$

which states that the equation is to be minimized with respect to x. The terms λ and D are the control parameter and a second order difference matrix respectively. Minimizing the first term in equation (2) forces output to be similar to the original noisy signal. Minimization of second term leads to noise removal by smoothing the signal. So, λ is used to control the degree of smoothness and holding similarity to the noisy signal. Solving the Least Square problem leads to the following result

$$x = (\mathbf{I} + \lambda \mathbf{D}^T \mathbf{D})^{-1} y \tag{3}$$

For denoising 2D signal, i.e. an image, the LS solution is first applied on the columns of the 2D matrix, then applied on its rows. So, the procedure of denoising with Least Square is a matter of a simple matrix operation. It makes computation complexity to be reduced and requires lesser time to denoise when compared to techniques like Legendre-Fenchel and Wavelet denoising.