SUPER-RESOLUTION RECONSTRUCTION OF HYPERSPECTRAL IMAGES VIA AN IMPROVED MAP-BASED APPROACH

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ABSTRACT

Super-resolution Reconstruction (SRR) is technique to increase the spatial resolution of images. It is especially useful for hyperspectral images (HSI), which have good spectral resolution but low spatial resolution. In this study, we propose an improvement to our previous work and present a novel MAP-MRF (maximum a posteriori-Markov random Fields) based approach for the SRR of HSI. The key point of our approach is to find the abundance maps of an HSI and perform SRR on the abundance maps using MRF based energy minimization, without needing any other additional source of information. In order to do so, first, PCA is used to determine the endmembers. Second, SISAL and fully constraint least squares (FCLS) are used to estimate the abundance maps. Third, in order to find the high resolution abundance maps, the ill-posed inverse SRR problem for abundances is regularized with a MAP-MRF based approach. The MAP-MRF formulation is restricted with the constraints which are specific to the abundances. Using the non-linear programming (NLP) techniques, the convex MAP formulation is minimized and High Resolution (HR) abundance maps are obtained. Then, these maps are used to construct the HR HSI. This improved SRR method is verified on real data sets, and quantitative performance comparison is achieved using PSNR, SSIM and PSNR metrics. Our results indicate that this improved method gives very close results to the original high resolution images, keeps the spectral consistency, and performs better than the compared algorithms.

Index Terms— Hyperspectral, Super-resolution Reconstruction, MAP-MRF, Non-Linear Programming

1. INTRODUCTION

Hyperspectral images (HSI) have the desirable property of having a high spectral resolution; however, their low spatial resolution degrades their performance in remote object detection, object recognition and material discrimination [1][2]. In the literature, several algorithms have been proposed to enhance the spatial resolution of HSI. A popular approach is to use image fusion, in which spatial information of RGB or multispectral image is fused with a LR HSI [3][4]. The main drawback of this approach is the difficulty to obtain an HR image in addition to the HSI. Another approach used in SRR of HSI is based on spectral mixture analysis. Linear unmixing is used for endmember and abundance estimation, which are in turn used for obtaining HR land cover maps. In such approaches, a general practice is to split the pixels into subpixels according to a zoom factor and to find the subpixel positions [5]. In these studies, subpixels are assumed to be composed of pure pixels which may not be an accurate assumption [6]. A third viewpoint is to use learning based approaches for the SRR of HSI [7]. In general, the main advantage of learning based methods is that they provide a natural way of obtaining the required image characteristics, however, training requires a long learning time that severely limits their applications and the performance highly depends on the similarity between training data set and test data set. In this paper, we extend the study of [8] and propose an improved novel approach to enhance the resolution of HSI. The basis of the proposed SRR is the spatial correlation of the endmembers and the inherent properties of the abundance maps. The proposed method is not applied in the spectrum domain since considering the bands separately does not make use of the information that is present across them. Furthermore, separate band SRR does not make use of the inherent low dimensionality of the spectral data, which can effectively improve the robustness against noise.

This study is different from our previous work on four folds: (i) we do not make a pure pixel assumption in this work, (ii) we do not use graph cuts but solve our joint energy optimization term with quadratic programming, (iii) use the basic PCA principles in selecting the number of endmembers as opposed to providing them as input and (iv) we evaluate our results quantitatively as opposed to qualitatively. The second improvement, namely reformulating our joint energy minimization as a quadratic optimization problem increased both the SNR rates of our algorithm and its speed significantly. The experiments on real data and comparative analysis show the effectiveness of the proposed method.

2. METHODOLOGY

The proposed method consists of two main parts namely Spectral Unmixing and Joint Energy Minimization. In the first part, Low Resolution (LR) abundance maps are estimated. In the second part, the MAP-MRF based energy function is jointly minimized for all abundance maps and HR abundance maps are obtained using NLP methods. We will give a detailed description of each part in this section.

2.1. Spectral Unmixing

Spectral unmixing determines the relative abundance of materials that are depicted in multispectral or hyperspectral imagery. First step in linear unmixing is the estimation of number of endmembers in the image. Because of the lack of knowing ground truth, generally the number of endmembers is not known and should be estimated as accurate as possible. The number of endmembers can be estimated through supervised (user-selected) or unsupervised (automated) algorithms [9]. Supervised approaches require the user to count or select pixels which represent the different materials in the image [10]. Unsupervised approaches use the dimensionality of the image data as the basis for estimating the number of endmembers [11]. A common supervised method is principal component analysis (PCA). In PCA, an estimate for the number of endmembers is given by the number of eigenvectors which contains a user-defined percentage of image variability [12]. This concept is used to estimate the number of endmembers in the image using the defined percentage as 99%. In other words, number of endmembers (i.e. "e") is the smallest number that holds the inequality in (1). In (1), "λ_i" is showing the eigenvalues of the hyperspectral data, and "p" shows the number of spectral bands.

$$\frac{\sum_{j=1}^{e} \lambda_j}{\sum_{i=1}^{p} \lambda_i} \geq 0.99 \qquad (1)$$

After number of endmembers is estimated, the endmember signatures can be extracted. Extraction algorithms can be divided into two groups [13]. In the first group, it is assumed that pure pixels are present in the image for each endmember. PPI, VCA and NFINDR are the most common endmember extraction algorithms with pure pixel. However, in our tests, we figured out that applying blur operation may corrupt pure pixels in the image. Therefore, using an algorithm without the pure pixel assumption is more suitable in this application. In [14], the endmember extraction algorithms without pure pixel assumption are compared. According to the results, Splitted Augmented Lagrangian (SISAL) has better performance than MINVEST, MVC-NMF, MVES, MVSA algorithms. Therefore, in this study, SISAL is used for endmember extraction. In SISAL, the unmixing is achieved by finding the minimum volume simplex containing the hyperspectral data. This optimization problem was solved by a sequence of variable splitting augmented Lagrangian optimizations [15].

In order to estimate the abundance maps, we use fully constraint least squares (FCLS) for the accurate material quantification [16].

2.2. Joint Energy Minimization

As a good starting point, we can use the super-resolution model. The matrix notation used to formulate the super resolution model of the problem in the pixel domain is:

$$\boldsymbol{Y = DBZ + n} \qquad (2)$$

where,
Y: LR Image, Z: HR Image, D: Downsampling Operation, B: Blur Operation, n: Noise
Therefore, the inverse problem to be minimized is:

$$\|\boldsymbol{DBZ - Y}\|_2^2 \qquad (3)$$

In (3), $|.|_2$ is L2 norm. This inverse problem is ill-posed since the information of LR image does not give enough information to recover HR image. In hyperspectral imaging, the function to be minimized for p spectral bands is:

$$\sum_{i=1}^{p} \|\boldsymbol{DBZi - Yi}\|_2^2 \qquad (4)$$

From the linear mixture model in hyperspectral imaging, we know that:

$$\boldsymbol{Z = A_z . S} \qquad (5)$$

$$\boldsymbol{Y = A_y . S} \qquad (6)$$

Thus, the Spectral Signature Matrix (i.e. S) has no effect on the minimization of (4), thus the expression becomes:

$$\sum_{i=1}^{E} \| DBz(e) - y(e) \|_2^2 \quad (7)$$

Since SRR using only (7) is an ill-posed problem (i.e. unique solution does not exist), a regularization term is needed to compensate the missing solution. Actually, regularization is implemented as a penalty factor in the cost function. We use a MAP-MRF approach for the regularizer using (8):

$$\sum_{k=1}^{N} \sum_{j=1}^{4} \left\| z(k) - z_{clique}(k)(j) \right\|_2^2 \quad (8)$$

Moreover, we extend the regularizer in (8) for each endmember and obtain a joint MAP-MRF approach.

$$\sum_{i=1}^{E} \sum_{k=1}^{N} \sum_{j=1}^{4} \left\| z(e)(k) - z_{clique}(e)(k)(j) \right\|_2^2 \quad (9)$$

In (8), z_{clique} shows the 4-neighbourhood of the $z(e)(k)$. Combining regularizer with the inverse problem, we obtain (10), in which λ is the regularization factor.

$$\sum_{i=1}^{E} \| DBz(e) - y(e) \|_2^2 + \lambda \sum_{i=1}^{E} \sum_{k=1}^{N} \sum_{j=1}^{4} \left\| z(e)(k) - z_{clique}(e)(k)(j) \right\|_2^2 \quad (10)$$

After rearranging the terms in (10), we obtain the final energy function in the format given in (11). In (11), H is a symmetric matrix describing the coefficients of the quadratic terms and f is a row vector describing the coefficients of the linear terms in the energy function.

$$E(z) = \frac{1}{2} z^T H\, z + f^T z \quad (11)$$

Using NLP algorithms, we minimize (11) subject to the sum-to-one constraint specific to the abundance maps; and obtain the HR abundance maps are obtained. Finally, by using HR abundance maps and the spectral signature of endmembers, HR HSI is constructed.

3. EXPERIMENTS

We applied the proposed method to different datasets. The first database, called Harvard [17], has 50 indoor and outdoor images recorded under daylight illumination, and 27 images under artificial or mixed illumination. The spatial resolution of these images is 1392×1040 pixels, with 31 spectral bands of width 10 nm, ranging from 420 to 720 nm. The second data set is Stanford [18] which consists of 15 images which are faces of different people. The spatial resolution is different for each image but it is close to the first database. However, this database has 148 spectral bands spanning 415 to 950 nm in steps of 4. For both databases, we select patches from the images with various sizes. The original patches in the databases serve as ground truth. To obtain LR HSI, we blurr, downsample and add 30 dB Gaussian noise to the HR HSI. Then, use this LR HSI as the input image to the proposed method. The quantitative performance comparison is done via the PSNR, SSIM and SAM metrics. In Figure-1, and 2, the resulting reconstructed HR images are given with original and bicubic interpolated of LR images. In these figures, PSNR, SSIM, SAM values are also given to evaluate the quantitative performance of the proposed method.

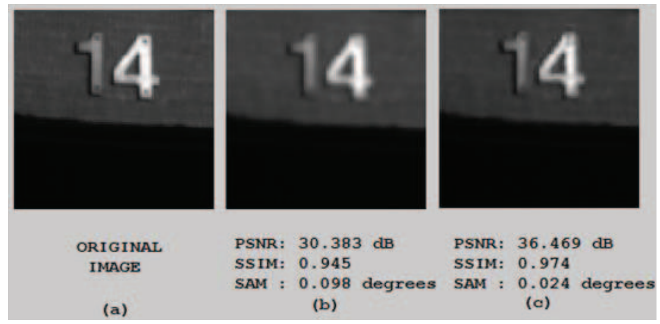

Figure -1, (a) Original HR Image
(b) Bicubic Interpolated Image
(c) Output of the Proposed Method

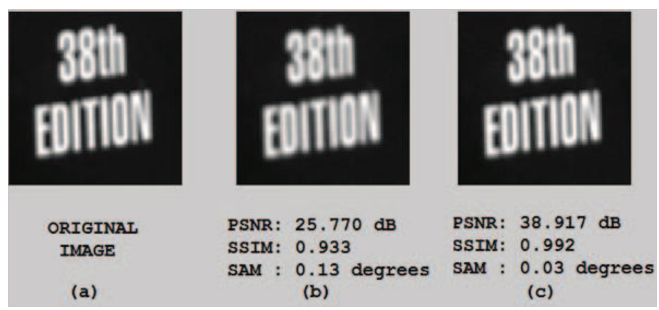

Figure -2, (a) Original HR Image
(b) Bicubic Interpolated Image
(c) Output of the Proposed Method

Upon investigating the figures above, it can be seen that the proposed method is doing better than the bicubic interpolation method in both the PSNR, SSIM amd SAM metrics; and edges are retained. A further advantage of our method is that it keeps spectral consistency since our approach does not change the spectral signatures but only the abundance maps.

4. CONCLUSION

In this work, an improved MAP-MRF based method to enhance the spatial resolution of hyperspectral images has been proposed. First, using PCA number of endmembers in the image is estimated. Then, using SISAL, endmembers are extracted, and LR abundance maps are obtained using FCLS. After LR abundance maps are estimated, solving a

MAP-MRF based joint energy minimization using non-linear programming techniques, HR abundance maps are found and combined to get HR hyperspectral image. Experiments are carried out on real data and show satisfactory results. The quantitative performance comparison is achieved using the common performance metrics.

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