A COMBINED HYPERSPECTRAL IMAGE RESTORATION AND FUSION APPROACH

Yifan Zhang, Arno Duijster, and Paul Scheunders

IBBT, Vision Lab, Department of Physics
University of Antwerp, 2610 Wilrijk, Belgium
Email: yifan.zhang@ua.ac.be; arno.duijster@ua.ac.be; paul.scheunders@ua.ac.be

1. INTRODUCTION

Due to physical limitations, data-transfer requirements and other reasons, usually a trade-off exists between SNR, spatial and spectral resolutions in remote sensors. In most cases, high spatial and spectral resolutions are not available in a single image. For example, the spatial resolution of hyperspectral (HS) images is usually lower than that of multispectral (MS) images [1]. In practice, many applications require high accuracy both spatially and spectrally, which inspires research on HS image spatial resolution enhancement techniques. In this paper, we study how to optimize the spatial resolution of an HS image by using a low-resolution HS observation and a high-resolution MS observation of the same scene.

In the recent literature, different techniques were developed for enhancing the spatial resolution of HS images. One way of dealing with the problem is image fusion, in which an image of high spectral resolution is combined with an image of high spatial resolution. In most cases, an MS image is fused with a panchromatic image [2]. In [1] and [3], 2D and 3D wavelet based HS and MS image fusion approaches were proposed. Statistical estimation based techniques were also developed. In [4], Hardie *et al* presented a MAP estimation framework for enhancing the spatial resolution of HS image using co-registered high spatial-resolution imagery from an auxiliary sensor.

Another approach is image restoration, in which the spatial resolution of an image is enhanced by inverting the imaging model using the image point spread function. In [5] , an Expectation-Maximization algorithm (EM algorithm) based image restoration scheme is proposed, in which a deconvolution step and a denoising step are applied separately. Duijster *et al* extended this work to MS image restoration [6].

In this work, we present a new approach for HS image spatial resolution enhancement, which combines both approaches of fusion and restoration. The image fusion technique of [4] is combined with the EM-based restoration technique of [6]. In this way, the spatial resolution of an HS image is improved by knowledge of the images point spread function and by using an MS image of higher spatial resolution. Simulation experiments with a reference are performed, in which the method is evaluated against the pure deconvolution method as well as the image fusion method.

2. METHOD

Let $\mathbf{S}$ denote an HS image, modeled by the observation model:

$$\mathbf{Y} = \mathbf{WS} + \mathbf{N} \tag{1}$$

with $\mathbf{Y}$ the observed HS image, $\mathbf{W}$ a known linear system operator and $\mathbf{N}$ additive white noise with covariance matrix $\mathbf{C_n}$. The estimation of $\mathbf{S}$ is actually an image restoration problem. In [6], the deblurring and denoising are performed in two separate steps. To accomplish this, (1) is decomposed as

$$\mathbf{Y} = \mathbf{WX} + \mathbf{N}_2 \tag{2}$$

$$\mathbf{X} = \mathbf{S} + \mathbf{N}_1 \tag{3}$$

where $\mathbf{WN}_1 + \mathbf{N}_2 = \mathbf{N}$ with $p(\mathbf{N}_1) = \phi(0, \mathbf{C_n})$ and $p(\mathbf{N}_2) = \phi(0, \mathbf{C_n} - \mathbf{WC_nW}^T)$. The spatial-invariance of $\mathbf{W}$ guarantees a semi positive-definite covariance for $\mathbf{N}_2$. If $\mathbf{W}$ would be not translation-invariant, a rescaling is required (see [5]). In this way, all coloring of the noise, due to $\mathbf{W}$ is put into $\mathbf{N}_2$. When $\mathbf{N}_2$ is assumed to be small, the denoising problem is shifted towards the second equation. As a result, the original problem has been split up into a deblurring problem (2) and a denoising problem (3).

The estimation is implemented iteratively, using the EM algorithm. At each iteration k, an estimate $\hat{\mathbf{X}}^{(k)}$ is obtained from inverting (2), using an estimate of $\hat{\mathbf{S}}^{(k-1)}$ from the previous iteration, after which a new estimation $\hat{\mathbf{S}}^{(k)}$ is obtained from (3). We solve the deconvolution problem of (2) by estimating $\mathbf{X}$ in a Bayesian framework using the observed image $\mathbf{Y}$ and a high spatial resolution MS image $\mathbf{H}$ as an auxiliary. At each iteration, the estimation comes down to the calculation of:

$$\hat{\mathbf{X}}^{(k)} = \arg\max_{\mathbf{X}} p(\mathbf{X}|\mathbf{Y}, \mathbf{S}^{(k-1)}, \mathbf{H}) \tag{4}$$

When a normal model is assumed for the joint pdf of $\mathbf{S}$ and $\mathbf{H}$, then one obtains after some calculation:

$$\hat{\mathbf{X}}^{(k)} = \mathbf{M} + \mathbf{B}\mathbf{W}^T(\mathbf{C_n} - \mathbf{W}\mathbf{C_n}\mathbf{W}^T + \mathbf{W}\mathbf{B}\mathbf{W}^T)^{-1}(\mathbf{Y} - \mathbf{W}\mathbf{M}) \tag{5}$$

with

$$\begin{aligned} \mathbf{B} &= (\mathbf{C_n}^{-1} + \mathbf{C}_{\mathbf{X}|\mathbf{H}}^{-1})^{-1} && (6) \\ \mathbf{M} &= \mathbf{B}[\mathbf{C_n}^{-1}\hat{\mathbf{S}}^{(k-1)} + \mathbf{C}_{\mathbf{X}|\mathbf{H}}^{-1}\boldsymbol{\mu}_{\mathbf{X}|\mathbf{H}}] && (7) \end{aligned}$$

where $\boldsymbol{\mu}_{\mathbf{X}|\mathbf{H}}$ and $\mathbf{C}_{\mathbf{X}|\mathbf{H}}$ are the mean and covariance matrix of $\mathbf{X}$ conditioned on $\mathbf{H}$

$$\begin{aligned} \boldsymbol{\mu}_{\mathbf{X}|\mathbf{H}} &= \mathbf{E}(\mathbf{X}) + \mathbf{C}_{\mathbf{X},\mathbf{H}}\mathbf{C}_{\mathbf{H},\mathbf{H}}^{-1}[\mathbf{H} - \mathbf{E}(\mathbf{H})] && (8) \\ \mathbf{C}_{\mathbf{X}|\mathbf{H}} &= \mathbf{C}_{\mathbf{X},\mathbf{X}} - \mathbf{C}_{\mathbf{X},\mathbf{H}}\mathbf{C}_{\mathbf{H},\mathbf{H}}^{-1}\mathbf{C}_{\mathbf{X},\mathbf{H}}^T && (9) \end{aligned}$$

It is important to note that the estimation of $\boldsymbol{\mu}_{\mathbf{X}|\mathbf{H}}$ and $\mathbf{C}_{\mathbf{X}|\mathbf{H}}$ requires $\mathbf{X}$. The denoising step of the iteration is accounted for by replacing $\mathbf{X}$ with $\mathbf{S}^{(k-1)}$ in the estimation of these parameters (and adding $\mathbf{C_n}$ to the covariance). In this work, we also present a practical implementation of this iterative algorithm.

3. EXPERIMENTS

Experiments are carried out to verify the correctness and effectiveness of the newly proposed method. A simulated data set is obtained by degrading an original HS image in the spectral direction to obtain a simulated MS image and in the spatial domain to obtain a simulated HS image. The simulated results are compared to the pure deconvolution result of [6] and the fusion result of [4]. The experimental results illustrate that the proposed deconvolution and fusion approach outperforms the other two. It is capable of enhancing the spatial resolution of the observed HS image effectively, preserving spectral features, as well as reducing additive noise.

4. REFERENCES

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