BAYESIAN IMAGE SHARPENING

Sang-Hoon Lee
Department of Industrial Engineering
Kyungwon University
Seongnam-si, Gyeonggi-do 461-701, Korea
shl@kyungwon.ac.kr

ABSTRACT

Up to now the satellite imagery with very-high resolution of less than or equal to 1m resolution can be obtained from panchromatic sensors, while multispectral data are available only with mid-high or moderate spatial resolution. Image fusion techniques can effectively integrate the spatial detail of panchromatic data and the spectral characteristics of multispectral images. It is important for human's visual interpretation or computer's autonomous recognition to improve the accuracy in analyzing land-cover types. The synthesis process of multispectral images to the higher resolution of the panchromatic image is called "pan-sharpening" of multispectral images. Most of the pan-sharpening techniques have been designed to minimize the spectral distortion in the synthetic multispectral image of the higher resolution. However, the fusion process results in a block distortion at the boundary of the synthetic multispectral image. The image sharpening process proposed in this study is aiming at minimizing the spectral distortion as well as eliminating the block distortion. The proposed scheme is an optimization process using a Bayesian objective which includes a Gibbs random field (GRF). The GRF is employed to use the contextual information of panchromatic image for relaxing the block distortion. The fusion process should generate the synthesis of multispectral image at the higher resolution of the panchromatic image, which agrees with the observed spectral values. For this purpose, the optimization is subject to the constraint that the spectral response of a pixel in the lower resolution is equal to the average response of the pixels belonging to the corresponding area in the higher resolution at a same wavelength. The new method has been applied to the IKONOS and KOMPSAT-2 images acquired over an area of the Korean peninsula.

INTRODUCTION

The techniques to integrate panchromatic and multispectral data have mainly been developed for the application to generate a RGB image of the higher spatial resolution of the panchromatic image. For this application, the IHS technique (Chavez and Anderson, 1991) and Brovey transform (Civco *et al*., 1995) have been most widely used in practice. The fusion techniques have been designed to obtain the synthetic images similar to the multispectral images that would have been observed from a sensor of the higher resolution. The synthesis process of multispectral images to the higher resolution of the panchromatic image is called "pansharpening" of multispectral images. Zhang and Hong (2005) assorted the algorithms for pansharpening into three categories: 1) projection and substitution methods, such as IHS technique 2) band ratio and arithmetic combination, such as Brovey Transformation, and 3) fusion method which injects spatial features of a panchromatic image into multispectral images. The injection method was earlier developed by using high-pass filtering to extract the spatial features, and later multiresolution analysis such as wavelet and Laplacian pyramids (Yocky, 1995; Nunez *et al*., 1999; Aiazzi *et al*., 2002) has been employed for detail injection. The eight algorithms recently developed and provided by seven research teams were compared with a standardized evaluation procedure (Alparone *et al*., 2006). In their experiments, two algorithms, generalized Laplacian pyramid with context-based decision method (Aiazzi *et al*., 2006) and additive wavelet luminance proportional method (Otazu, *et al*.), outperformed all others. They showed that the algorithms based on multiresolution analysis generally performed better than ones based on component substitution.

Most recently, the quadratic programming method was suggested to generate the synthesis of multispectral image at the higher resolution of the panchromatic image, which agrees with the observed spectral values (Lee, 2008). This scheme reconstructs the multispectral image at the higher resolution using the regression model fitting the panchromatic spectral values to the observed multispectral data. This study used the pansharpening method, FitPAN(Fitting to Panchromatic Image for Pansharpening), which is a modified version of the quadratic programming method. It aims at minimizing or reducing the spectral distortion in the synthetic multispectral image of the higher resolution. However, the fusion process results in a block distortion at the boundary of the synthetic multispectral image. A sharpening process is proposed to eliminate the block distortion using the contextual information of the panchromatic image and the Point-Jacobian MAP iteration (Lee, 2007). The new method was applied to the IKONOS 1m panchromatic image of 2400×2400 and 4m multispectral images of 600×600 acquired over the area around Anyang City of Korea.

FitPAN

Let z_j be the multispectral vector of the *j*th pixel in the synthetic image similar to the multiband image that would have been observed from a multispectral sensor with the higher resolution of the panchromatic image. The image model is usually assumed to be additive Gaussian. Under this assumption, given μ_j and Σ_j as the mean multispectral vector and its covariance matrix of the *j*th pixel in the multispectral image at the higher resolution, the objective function for the maximum likelihood estimates of $\{z_j\}$ is:

$$\underset{\{z_j\}}{\mathrm{Max}}\left[\prod_{\forall j}\Pr(z_j \mid \mu_j, \Sigma_j)\right]. \tag{1}$$

In the fusion, it is supposed that one pixel of the lower resolution can be divided into k^2 pixels of the higher resolution for an integer *k*. If $K = k^2$ and the $i(j)$ th pixel means the *j*th pixel of the higher resolution belonging to the *i*th pixel in the lower resolution,

$$\prod_{\forall i}\left[\underset{\{z_{i(j)}\}}{\mathrm{Max}}\left[\prod_{j=1}^{K}\Pr(z_{i(j)} \mid \mu_{i(j)}, \Sigma_{i(j)})\right]\right]. \tag{2}$$

The optimization of Eq. (2) can be considered independently for each pixel of the lower resolution, and equivalently,

$$\underset{\{z_{i(j)}\}}{\mathrm{Min}}\sum_{j=1}^{K}(z_{i(j)} - \mu_{i(j)})^T \Sigma_{i(j)}^{-1}(z_{i(j)} - \mu_{i(j)}), \quad \forall i. \tag{3}$$

In image processing, it is supposed that the intensity of each pixel corresponds to the average brightness which arises from the random emission of discrete particles (called photons) with identical energy. In terms of the number of photons, the spectral response of a pixel in the lower resolution is assumed to be equal to the average response of the pixels belonging to the corresponding area in the higher resolution at a same wavelength. For this assumption, the objective of Eq. (3) must be subject to:

$$\frac{1}{K}\sum_{j=1}^{K} z_{i(j)} = z_i^{Low}. \tag{4}$$

where z_i^{Low} is the observed multispectral vector of the *i*th pixel in the lower resolution. If the covariance matrix of multispectral vector is constant in a same pixel of the lower resolution, the optimization problem for the maximum likelihood estimates of $\{z_j\}$ can be restated using a Lagrangian coefficient vector:

$$\underset{\{z_{i(j)}\}}{\mathrm{Min}}\ \sum_{j=1}^{K}\frac{1}{2}(z_{i(j)} - \mu_{i(j)})^T \Sigma_i^{-1}(z_{i(j)} - \mu_{i(j)}) + \lambda^T (K z_i^{Low} - \sum_{j=1}^{K} z_{i(j)}). \tag{5}$$

The optimal solution is obtained by solving a linear equation system of the first derivatives with respect to $\{z_{i(j)}\}$ and λ in Eq. (5):

$$\hat{z}_{i(j)} = \mu_{i(j)} + \sum_{j=1}^{K} (z_i^{low} - \overline{\mu}_i), \quad j = 1,2,\cdots,K$$
$$\overline{\mu}_i = \frac{1}{K} \sum_{j=1}^{K} \mu_{i(j)} \quad . \tag{6}$$

The true mean vector, $\{\mu_{i(j)}\}$, is not known in most application. Lee (2008) suggested that the mean vector can be estimated based on the observation using a polynomial regression model of order *p*:

$$\mu_{i(j)} = \sum_{k=0}^{p} \beta_k x_{i(j)}^k \ . \tag{7}$$

where $x_{i(j)}$ is the observed value of the $i(j)$ th pixel from the higher resolution sensor and β_k are the *k*th polynomial coefficient vector. From Eqs. (6) and (7), a pansharpening scheme, so called FitPAN, is established:

$$\begin{bmatrix} \hat{B}_{i(j)} \\ \hat{G}_{i(j)} \\ \hat{R}_{i(j)} \\ \hat{N}ir_{i(j)} \end{bmatrix} = \begin{bmatrix} \hat{\mu}_B(P_{i(j)}) + \delta_i^B \\ \hat{\mu}_R(P_{i(j)}) + \delta_i^G \\ \hat{\mu}_G(P_{i(j)}) + \delta_i^R \\ \hat{\mu}_{Nir}(P_{i(j)}) + \delta_i^{Nir} \end{bmatrix}$$
$$\hat{\mu}_M(P_{i(j)}) = \sum_{k=0}^{p} \hat{\beta}_M^k P_{i(j)}^k$$
$$\delta_i^M = \sum_{j=1}^{K} \mu_M(P_{i(j)}) - M_i \quad . \tag{8}$$

where $P_{i(j)}$ is the $i(j)$ th pixel's value of panchromatic image of the higher resolution and M_i the *i*th pixel's value of *M* band multispectral image of the lower resolution.

BAYESIAN IMAGE RESTORATION

The experimental results of Section 3 show that FitPAN reduced the distortion of spectral information compared to the other methods. However, block distortion was appeared on the boundary in the synthetic multispectral image at the higher resolution of the panchromatic image. To correct this problem, a sharpening process of the Point-Jacobian Iteration MAP (PJIMAP) estimation (Lee and Crawford, 1991; Lee, 2007) is proposed in this study. The proposed scheme is designed to utilize the contextual information of the original panchromatic image.

Given an observed image Y, the Bayesian method is to find the MAP estimate from the mode of the posterior probability distribution of the original image X, or equivalently, to maximize the log-likelihood function. The log-likelihood function using a Gaussian image model and MRF texture model is:

$$\ell PN \propto -(Y - X)'\Sigma^{-1}(Y - X) - X'\mathbf{B}X \tag{9}$$

where $\Sigma = diagonal\{\Sigma_i\}$ is the covariance matrix of the Gaussian image model and $\mathbf{B} = \{\beta_{ij}\}$ is the bonding strength matrix which is associated with local interaction between neighbouring pixels. If the bonding strength is only dependent on spatial location, β_{ij} is constant and $\mathbf{B} = \{\beta_{ij}\mathbf{I}_m\}$ where *m* is the number of bands and $\mathbf{I}_m$ is the *m*-

dimensional identity matrix. Since the log-likelihood function is convex, the MAP estimate of X is obtained by taking the first derivative, and then using the Point-Jacobian iteration, the original image can be recovered iteratively: if each band has a same bonding strength, at the hth iteration (Lee, 1991)

$$\hat{x}_i^h = (\Sigma_i^{-1} + \beta_{ii})^{-1}\left(\Sigma_i^{-1} y_i - \sum_{(i,j)\in C_p} \beta_{ij}\hat{x}_j^{h-1}\right) \tag{10}$$

where C_p is the pair-clique system of $\{I_n, R\}$ if R a "neighbourhood system" for the image index system, I_n .

To correct block distortion in pansharpening, the bonding strength coefficients, β_{ij} , are estimated using the original panchromatic data. For $\hat{\beta}_{ij} = \hat{\phi}_i \hat{\alpha}_{ij}$ (Lee, 2007),

$$\begin{aligned} \hat{\phi}_i &= \sqrt{\frac{r}{\sigma_i^2 \sum_{(i,j)\in C_p} \hat{\alpha}_{ij}(P_i - P_j)^2}} \\ \hat{\alpha}_{ij} &= \begin{cases} \dfrac{(P_i - P_j)^{-2}}{\sum_{(i,k)\in C_p}(P_i - P_k)^{-2}} & \text{for } (i,j)\in C_p \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{11}$$

where P_i and σ_i^2 are the spectral value and variance of the ith pixel in the panchromatic image respectively. The bonding strength coefficients estimated from Eq. (11) represents local interaction between neighbouring pixels and can provide some contextual information on the local region in the panchromatic image. Given an initial vector, $\hat{x}_i^0 = y_i$ where $\{y_i\}$ is a synthetic multispectral image generated from pansharpening, the iteration of Eq. (10) generates an image $\{\hat{x}_i\}$ sharpened based on spatial texture of the panchromatic image.

For this sharpening process, r in Eq. (11) and the window size for the neighbourhood system should be determined. To examine the effect of these parameters on the results of the sharpening process, the experiment was performed with various values of r and the window size for the degraded images same as in the previous section. The sharpening process was applied to the FitPAN-fused image with significant block distortion as shown in Figure 1.

CONCLUSION

The pansharpening method of multispectral image of, FitPAN was proposed to reconstruct at the higher resolution the multispectral images which agree with the spectral values observed from the sensor of the lower resolution. In the proposed scheme, a regression model represents the relation between panchromatic and multispectral images, and is utilized to estimate the true mean vector of multispectral image of the higher resolution based on the multispectral observation. The pansharpening is constructed under the constraint that the spectral response of a pixel in the lower resolution is equal to the average response of the pixels belonging to the corresponding area in the higher resolution at a same wavelength. However, some block distortions were appeared in the synthetic multispectral image fused by FitPAN. The sharpening process proposed in this study effectively eliminated the block distortions using the contextual information of the panchromatic image without changing quality of the fused image.

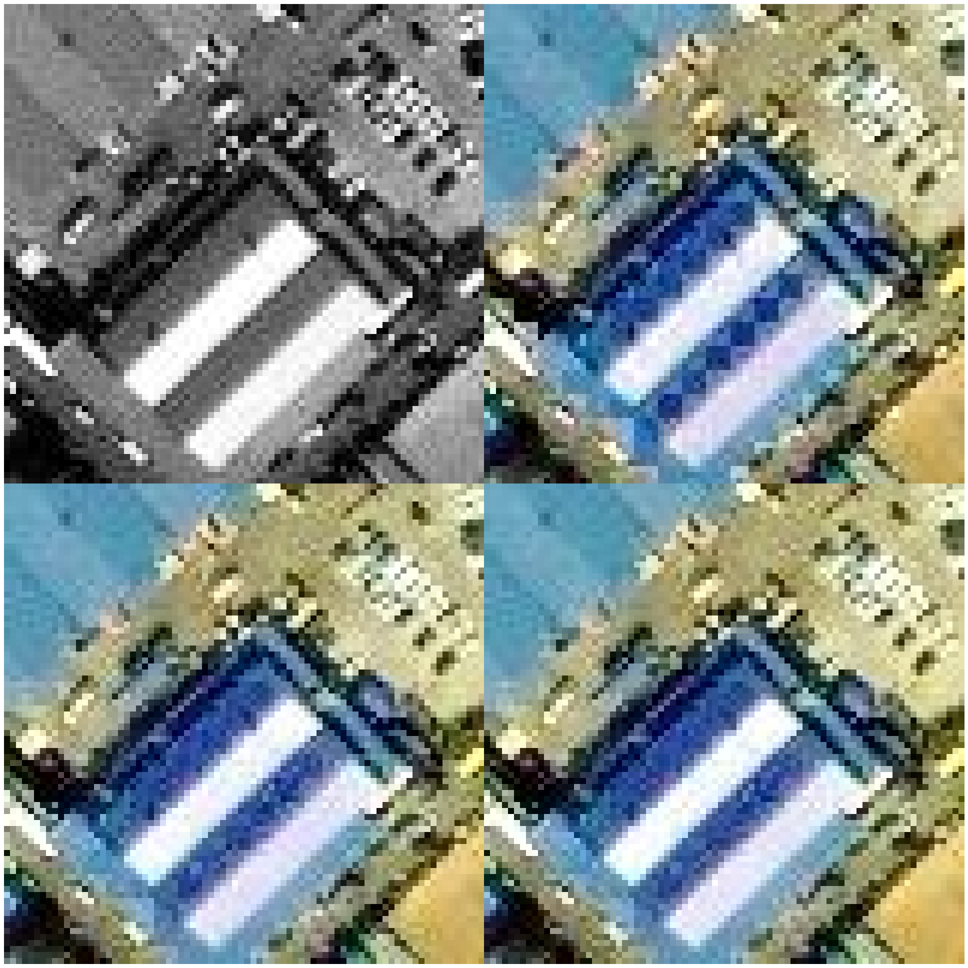

Figure 1. Results of sharpening process to remove block distortion(original panchromatic image and FitPAN-fused image before sharpening process in the top line, FitPAN-fused images after sharpening process of 7×7 window with r = 0.5 and 2.0 respectively from left in the bottom line).

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