IMAGE CLASSIFICATION OF HIGH RESOLTION MULTISPECTRAL IMAGERY VIA PANSHARPENING

Lee, Sang-Hoon

Kyungwon University, Korea
Email: shl@kyungwon.ac.kr

ABSTRACT : Lee (2008) proposed the pansharpening method to reconstruct at the higher resolution the multispectral images which agree with the spectral values observed from the sensor of the lower resolution values. It outperformed over several current techniques for the statistical analysis with quantitative measures, and generated the imagery of good quality for visual interpretation. However, if a small object stretches over two adjacent pixels with different spectral characteristics at the lower resolution, the pixels of the object at the higher resolution may have different multispectral values according to their location even though they have a same intensity in the panchromatic image of higher resolution. To correct this problem, this study employed an iterative technique similar to the image restoration scheme of Point-Jacobian iterative MAP estimation. The effect of pansharpening on image segmentation/classification was assessed for various techniques. The method was applied to the IKONOS image acquired over the area around Anyang City of Korea.

KEY WORDS: Pansharpening, Remote Sensing, Image Fusion, Panchromatic, Multispectral

1. INTRODUCTION

Lee (2008) proposed the pansharpening method to reconstruct at the higher resolution the multispectral images which agree with the spectral values observed from the sensor of the lower resolution values. It outperformed over several current techniques for the statistical analysis with quantitative measures, and generated the imagery of good quality for visual interpretation. However, if a small object stretches over two adjacent pixels with different spectral characteristics at the lower resolution, the pixels of the object at the higher resolution may have different multispectral values according to their location even though they have a same intensity in the panchromatic image of higher resolution. To correct this problem, this study employed an iterative technique similar to the image restoration scheme of Point-Jacobian iterative MAP estimation. The effect of pansharpening on image segmentation/classification was assessed for various techniques. The method was applied to the IKONOS image acquired over the area around Anyang City of Kore.

2. PANSHARPENING

The optimization problem of pansharpening in Lee (2008) is extended to a multidimensional form:

$$\underset{\{z_{i(j)}\}}{\text{Min}} \sum_{j=1}^{K} (z_{i(j)} - \mu_{i(j)})^T \Sigma_{i(j)}^{-1} (z_{i(j)} - \mu_{i(j)})$$

subject to

$$\frac{1}{K}\sum_{j=1}^{K} z_{i(j)} = z_i^{Low}$$
$$LB \le z_{i(j)} \le UB .$$

where

- K: number of pixels of the lower resolution corresponding to a pixel of the higher resolution
- z_i^{Low} : observed intensity vector of the ith pixel in the lower resolution
- $z_{i(j)}$: observed intensity vector of the $i(j)$ th pixel in the higher resolution
- $\mu_{i(j)}$: mean intensity vector of the $i(j)$ th pixel in the higher resolution
- $\Sigma_{i(j)}$: covariance matrix of the $i(j)$ th pixel in the higher resolution
- LB : lower bound of the spectral value
- UB: upper bounds of the spectral value.

The $i(j)$ th pixel means the jth pixel of the higher resolution belonging to the ith pixel in the lower resolution. The image model is usually assumed to be additive Gaussian. Under this assumptions, given $\{\mu_{i(j)}\}$ and $\{\Sigma_{i(j)}\}$ as the mean intensity vectors and covariance matrices of pixels in the higher resolution, this optimization problem obtains the maximum likelihood estimates of the higher resolution pixels belonging to the ith pixel at the lower resolution:

$$\underset{\{z_{i(j)}\}}{\text{Max}} \prod_{\forall i(j)} \Pr(z_{i(j)}).$$

Lee (2008) proposed a quadratic programming (Gill *et al*, 1991) approach to solve the optimization problem. However, the quadratic programming approach may be inefficient for the reconstruction of large imagery. In the optimization problem, the second constraint of *LB* and *UB* is a loose constraint. If this constraint is ignored and the covariance is constant, the optimization problem can be restated using a Lagrangian coefficient vector since the objective function is convex and the constraint is linear:

$$\underset{\{z_{i(j)}\}}{\text{Min}} \sum_{j=1}^{K}\frac{1}{2}(z_{i(j)}-\mu_{i(j)})^T\Sigma_i^{-1}(z_{i(j)}-\mu_{i(j)}) + \lambda^T(Kz_i^{Low}-\sum_{j=1}^{K}z_{i(j)})$$

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

$$\Sigma_i^{-1}(z_{i(j)}-\mu_{i(j)})-\lambda=0, \quad j=1,2,\cdots,K$$

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

From this equation system, the maximum likelihood estimates of $\{z_{i(j)}\}$ is computed:

$$z_{i(j)}=\mu_{i(j)}+\sum_{j=1}^{K}(z_i^{low}-\overline{\mu}_i), \quad j=1,2,\cdots,K$$

$$\overline{\mu}_i=\frac{1}{K}\sum_{j=1}^{K}\mu_{i(j)}$$

The true intensity, $\{\mu_{i(j)}\}$, is not known in most application. Since the spectral characteristic of single band in the higher resolution sensor is to cover a broad range of wavelength spectrum in the lower resolution sensor, it is supposed that the true intensity of the higher resolution image is a function of the observed intensity of higher resolution sensor:

$$\mu_{i(j)}=f(x_{i(j)})$$

where $x_{i(j)}$ is the observed intensity of the $i(j)$ th pixel from the higher resolution sensor. In this study, the function can be estimated by regression analysis using a polynomial model of the *p*th order:

$$\mu_{i(j)}=R_M(x_{i(j)})=\sum_{k=1}^{p}\beta_k x_{i(j)}^k$$

where *M* represents one of multispectral bands {Blue, Green, Red, Nearinfra}. Thus, a pansharpening scheme, so called, FitPAN is established:

$$\begin{bmatrix}\hat{B}_{i(j)}\\ \hat{G}_{i(j)}\\ \hat{R}_{i(j)}\\ \hat{Nir}_{i(j)}\end{bmatrix}=\begin{bmatrix}\mu_B(P_{i(j)})+\delta_i^B\\ \mu_R(P_{i(j)})+\delta_i^G\\ \mu_G(P_{i(j)})+\delta_i^R\\ \mu_{Nir}(P_{i(j)})+\delta_i^{Nir}\end{bmatrix}$$

$$\delta_i^M=\sum_{j=1}^{K}\mu_M(P_{i(j)})^k-M_i$$

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

3. PANSHARPENING CORRECTION

As mentioned in Section 1, it is very possible that the pansharpening yields bad estimates for the pixels of a small or narrow object which stretches over two or more adjacent pixels in the lower resolution if they have much different spectral characteristics each other. To correct this problem, the image restoration method of Point-Jacobian Iteration MAP (PJIMAP) estimation (Lee, 2007) is proposed in this study.

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 the log-normal intensity model and the MRF texture model is:

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

where $\mathbf{B}=\{\beta_{ij}\}$ is the bonding strength 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 (Varga, 1962), the original intensity can be recovered iteratively: given an initial estimate, $\hat{x}_i^0$, at the h th iteration

$$\hat{x}_i^h=\frac{1}{\sigma_i^{-2}+\beta_{ii}}\left(\sigma_i^{-2}y_i-\sum_{(i,j)\in C_p}\beta_{ij}\hat{x}_j^{h-1}\right)$$

where C_p is the pair-clique system of $\{I_n,R\}$ if R a "neighborhood system" for the image index system, I_n. The bonding strength coefficients, β_{ij}, which are associated with local interaction between neighbouring pixels, are estimated for pansharpening correction using the panchromatic image of higher resolution. For $\hat{\beta}_{ij} = \hat{\phi}_i \hat{\alpha}_{ij}$,

$$\hat{\phi}_i = \sqrt{\frac{r}{\sigma^2 \sum_{(i,j)\in C_p} \hat{\alpha}_{ij} (y_i - y_j)^2}}$$

$$\hat{\alpha}_{ij} = \begin{cases} \dfrac{(y_i - y_j)^2}{\sum_{(i,k)\in C_p} (y_i - y_k)^2} & \text{for } (i,j) \in C_p \\ 0 & \text{otherwise} \end{cases}$$

where y_i is the observed value of the ith pixel in the panchromatic image of higher resolution. These equations for a single band are easily extended for multiband applications. The pansharpened image is then corrected by PJIMAP.

4. EXPERIMENTS

The pansharpening method with correction was first applied to IKONOS 1m panchromatic image of 2400×2400 and 4m multispectral images of 600×600 acquired over the area around Anyang City of Korea. The IKONO data of unsigned 11bit range from 0 to 2047. Next, using the algorithms of Lee (2006a, 2006b), this study performs the experiments to assess the effect of pansharpening for image segmentation/classification.

A performance comparison was carried out among six methods including the proposed scheme:

1) Simple Resampling (SRS)
2) Generalized IHS transformation (GIHS)
3) Gram-Schmit spectral sharpening method (GS) as implemented in ENVI (Laben and Brower, 2000)
4) Additive Wavelet Luminance Proportional (AWLP)
5) FitPAN
6) FitPAN with correction (FitPAN-C).

For performance evaluation, the experiments used three measures for a single band and three for multiband data (Garzelli and Nencini, 2007):

1) Root Mean Square Error (RMSE)
2) Correlation Coefficient (CC)
3) Q index (Q)
4) erreur relative globale adiménsionelle de synthese (ERGAS)
5) Spectral Angular Mapper (SAM)
6) Q4 index (Q4).

Since the multispectral observation from the corresponding sensor of the higher resolution is not available, it was suggested that the fusion methods are evaluated for the second and third conditions by applying to the images degraded with the ratio of the lower resolution to the higher resolution (Wald *et al.* 1997). In this experiment, the panchromatic and multispectral images are degraded to 4m and 16m, respectively. Table 1 shows the results of evaluation measurement for the six pansharpening techniques. As shown in the table, the FitPAN approaches outperformed over the other techniques. FitPAN-C corrected the problem mentioned in Introduction, and the boundary between objects appeared more clearly in the multispectral image of higher resolution of FitPAN-C than one of FitPAN.

5. CONCLUSIONS

Experiments were carried out on IKONOS data to assess the distortion due to the fusion process by comparing to several current pansharpening techniques. Experimental results show that the pansharpened images generated by FitPAN-C will yield better results for image segmentation /classification.

References

Gill, P. E., W. Murray, and M.H. Wright, 1991. *Numerical Linear Algebra and Optimization*, Vol. 1, Addison Wesley.

Lee, S-H, 2006a. RAG-based Image Segmentation Using Multiple Windows, *KJRS*, 22(6), pp. 601-612.

Lee, S-H, 2006b. RAG-based Hierarchical Classification, *KJRS*, 22(6), pp. 613-619.

Lee, S-H, 2007. Speckle Removal of SAR Imagery Using a Point-Jacobian Iteration MAP Estimation, *KJRS*, 23(1), pp. 33-42.

Lee, S-H, 2008. Quadratic Programming Approach to Pansharpening of Multispectral Images Using a Regression Model, *KJRS*, 24(3), 257-267.

Varga, R. S., *Matrix Iterative Analysis*, Englewood Cliffs, NJ: Prentice-Hall, 1962.

Wald, L., T. Ranchin, and M. Mangolini, 1997. Fusion of satellite images of different spatial resolutions: Assessing the quality of resulting images, *Photogramm. Eng. Remote Sens.*, 63, pp. 691-699.

Table 1. Results of Evaluation Measurement for Six Pansharpening Methods

RMSE	SRS	GIHS	GS	AWLP	FitPAN	FitPAN-C
B	144.66	241.68	115.96	89.47	92.62	92.76
G	182.92	237.91	130.02	92.09	89.99	89.93
R	220.66	241.58	145.40	113.64	99.48	98.93
Nir	220.79	228.74	137.02	119.77	92.39	93.08
CC	**SRS**	**GIHS**	**GS**	**AWLP**	**FitPAN**	**FitPAN-C**
B	0.8600	0.8994	0.9201	0.9489	0.9476	0.9475
G	0.8318	0.9308	0.9298	0.9600	0.9628	0.9627
R	0.7980	0.9373	0.9295	0.9519	0.9620	0.9624
Nir	0.7533	0.9421	0.9237	0.9387	0.9616	0.9612
Q	**SRS**	**GIHS**	**GS**	**AWLP**	**FitPAN**	**FitPAN-C**
B	0.8429	0.8743	0.8949	0.9487	0.9466	0.9473
G	0.8068	0.9043	0.9004	0.9581	0.9623	0.9627
R	0.7609	0.9020	0.9027	0.9457	0.9618	0.9619
Nir	0.7017	0.8707	0.8970	0.9245	0.9588	0.9579
Index	**SRS**	**GIHS**	**GS**	**AWLP**	**FitPAN**	**FitPAN-C**
ERGAS	6.2507	7.2463	4.1321	3.3621	2.8869	2.8864
SAM	2.0098	2.3320	1.7915	1.7099	1.5269	1.5200
Q4	0.7745	0.9028	0.9043	0.9452	0.9591	0.9592