RESOLUTION ENHANCEMENT FOR HYPERSPECTRAL DATA OF CHINA'S FIRST LUNAR ORBITER CHANG'E-I

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ABSTRACT

China's first lunar orbiter Chang'e-I (CE-1) has the capability to concurrently capture hyperspectral imagery with resolution of *200m* along with CCD imagery with a higher resolution of *120m*. To better serve for future lunar terrain exploration, and preparation work for the landing of probe vehicle, resolution of hyperspectral images from CE-1 needs to be enhanced. In order to make use of information from a high-resolution CCD sensor, this paper introduces a resolution enhancing method combining MAP estimation with SMM, and develops an iteration optimization algorithm and a Possion optimization algorithm. Through a set of experiments, it is demonstrated that the proposed method is more effective for practical use compared with conventional methods in resolution enhancement of hyperspectral imageries of CE-1.

Index Terms—Spatial and spectral enhancement, unmixing, lunar, Chang'e-1

1. INTRODUCTION

China's first lunar orbiter Chang'e-I (named after a legendary Chinese fairy that flew to the moon) was launched on October 24, 2007[1], with the capability to concurrently capture low spatial resolution (LR) hyperspectral imageries along with relatively high resolution (HR) CCD imageries. Hyperspectral imaging can acquire spectral information of lunar ground surface and could be used in a variety of applications such as material identification, land cover classification, etc. To better serve for the future lunar terrain exploration, and the preparation work for the landing of probe vehicle, resolution of hyperspectral images from CE-1 needs to be enhanced. Obviously, if resolution enhancement of hyperspectral imageries can be achieved with combination of information from HR CCD imageries for the same lunar area from CE-1, the information richness of the remote sensing system will be highly improved and it will allow for better analysis of various phenomena on the moon.

Joint processing of multi resolution imageries has been previously researched in the context of improving the spatial detail in multi/hyper spectral imagery, most of which have heritage in the sharpening of multispectral imagery based on HR panchromatic imagery, including component substitution [2], multiresolution methods [3], least squares estimation [4], and statistical methods [5]. These approaches generally have the effect of imposing the HR information onto the intensity component of the LR image, which can be very beneficial for human exploitation of multi/hyper spectral imagery. However, the extent of the spatial enhancement may be limited to the first principal component of the hyperspectral image and usually leads to spectral distortion [7].

Recently, maximum a posteriori (MAP) estimation has been proposed to perform HR hyperspectral image estimation using an auxiliary sensor [7] [8]. The MAP estimators have been shown to provide some spatial enhancement beyond the first principal component. And the SMM (Stochastic Spectra Mixing Model) has been proved to be applicable to provide decomposed spectral data and correlative statistics of MAP estimation for resolution enhancement [8]. And because of its merit in reservation of spectral information with no need for certain spectral endmembers, SMM is suitable for resolution enhancement of hyperspectral data from lunar orbiter.

The focus of this paper is developing solution to the spatial enhancement of hyperspectral images from Chinese CE-1 lunar orbiter while reserving the spectral information.

2. PROPOSED PROCESSING SCHEMATIC OF RESOLUTION ENHANCEMENT

As shown in Fig.1, the process schematic of resolution enhancement of CE-1 hyperspectral data with HR CCD image begins by Region-based SIFT (Scale-invariant feature transform) registration method to obtain the well aligned images from different sensors. Next, it makes use of prior classification and SMM unmixing model to obtain the statistics parameters, for the process of MAP estimation without explicitly knowledge of the spectral relationship between the two sensors. Then, two optimization methods,

This paper is sponsored by the National High Technology Research and Development Program "863" Program of China, No.2010AA122206.

iterative algorithm and Possion algorithm, are introduced to solve the MAP formulation in the case of unknown point spread function (PSF) between two sensors.

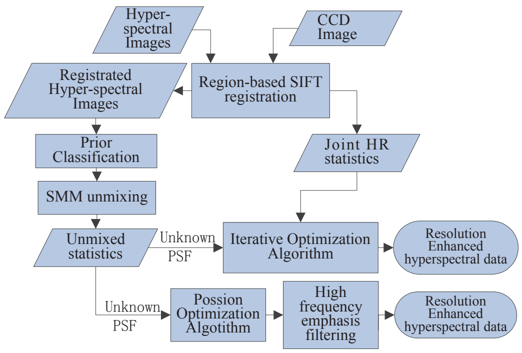


Fig.1 Process schematic of resolution enhancement of CE-1 hyperspectral data with HR CCD image.

3. KEY TECHNIQUES IN THE PROPOSED PROCESSING METHOD

3.1. Region-based SIFT Method for Registration

Sub-pixel accuracy in registration is necessary for satisfactory results of subsequent resolution enhancement processing. But topographic relief on lunar surface causes deformation between images from different sensors with different view angles, which cannot be simply specified by translations, rotations, or scales. Assuming that the relative position of features on lunar surface does not change, under the idea of region segmentation, the characteristic of SIFT algorithm can be used to registrate the LR hyperspectral and HR CCD Images without using artificially selected points:

(a). The CCD image is degraded to match the spatial resolution of hyperspectral images.

(b). The testing image of lunar surface area is divided into five regions: lunar surface bright area, lunar crater area, shadow region, slope area and the unclassified. Each region contains potential feature points.

(c). After eliminating unstable points, the dominant orientation and feature point description is found using the SIFT approach.

(d). Deleting error points, matching these feature points abstracted.

3.2. The Resolution Enhancement Model

The observed LR hyperspectral data cube B is an input of the enhancement formulation with M pixels per band, in which Y_j represents a U band spectral response at each spatial position j for $j = 1, 2, \dots, M$. Another input, $X = [x_1^T, x_2^T, \dots, x_N^T]^T$, where X_i represents the reflectance at each spatial position i for $i = 1, 2, \dots, N$, $M < N$, is the HR CCD data to estimate a desired image $Z = [z_1^T, z_2^T, \dots, z_N^T]^T$, representing the resolution enhanced hyperspectral image with U bands and N pixels per band. The vectors Z_i will be referred to as "hyper-pixels" which is a band-interleaved-by-pixel spatially rastered representation of the inherently data cube [7].

(a). The relationship of desired image Z and input Y can be expressed as

$$Y = HZ + n \tag{1}$$

where H is a sparse matrix with its rows are spatial response functions for the LR hyperspectral pixels, and n is a spatially independent zero-mean Gaussian random process with a spectral covariance matrix C_n.

(b). The relationship of Z and X can be expressed as

$$X = S^T Z + \eta \tag{2}$$

where the spectral response matrix S is a sparse matrix with columns are spectral response functions for the HR CCD pixel locations [3], and η is a spatially independent zero-mean Gaussian random process with a standard deviation of ρ_η.

3.3. MAP Estimation for Resolution Enhancement

Note that both H and S in the model in section3.2 are noninvertible, nonsquare matrices, no unique solution for Z in either equation can be derived, even in the absence of observation noise. In this case, MAP estimation method can be practical to estimate Z.

3.3.1. Basic idea of MAP estimation

The goal of MAP estimation is to find an estimation Z as desired HR hyperspectral data that can maximizes its conditional probability relative to the two observations X and Y, or

$$\hat{z} = \arg\max_z [p_{z/x,y}(z/x,y)] \tag{3}$$

From the form of the probability density functions that compose (3), an objective function can be formed whose minimization will result in the optimal estimate. This objective function is given by

$$f(Z) = \frac{1}{2}\left((Y-HZ)^T C_n^{-1}(Y-HZ) + (Z-m_{Z/X})^T C_{Z/X}^{-1}(Z-m_{Z/X})\right) \tag{4}$$

This function is quadratic in Z, and therefore, a closed-form solution for the minimum can be readily obtained. By differentiating the objective function, the direct solution is found by solving the system of equations

$$G = -H^T C_n^{-1}(Y-HZ) + C_{Z/X}{}^{-1}(Z-m_{Z/X})$$
$$b = -H^T C_n{}^{-1} Y + C^{-1}{}_{Z/X} m_{Z/X}$$
$$G\hat{Z} = -b \tag{5}$$

To obtain the statistic parameters needed in (5), unmixing of the LR hyperspectral data is necessary.

3.3.2. SMM for $C_{Z/X}{}^{-1}$ and $m_{Z/X}$

The SMM unmixing model is introduced to the MAP estimation to provide the statistic parameters of $C_{Z/X}{}^{-1}$ and $m_{Z/X}$ in Equation (4) (5).

To initialize the statistic parameters of endmembers, including mean vectors and covariance matrix, the prior probabilities are set uniformly distributed and a prior classification is performed with a set of well-separated image spectra selected from the image by SAM method. The results of prior classifications are lunar crater, bright area, shadow region, slope area and unclassified area. The image spectra are classified into the mixture classes as

$$\omega_q = \sum_{m=1}^{N_c} a_{i,m}(q)\varepsilon_m \tag{6}$$

where $a_{i,m}$ is the abundance for the ith pixel, q represents the class index of the assumed spectra mixture and $m=1,2,\ldots N_c$ denotes the number of endmember for each class. Afterward, a series of iterations are performed in the following unmixing process.

Then the endmember mean and covariance estimates are updated by

$$m_{z_i} = \sum_{m=1}^{N_c} b_{i,m} m(\varepsilon_m),\ C_{z_i} = \sum_{m=1}^{N_c} b_{i,m}^2 C(\varepsilon_m) \tag{7}$$

where $b_{i,m}$ is interpolated by $a_{i,m}$. The results of (7) are inserted into (5) to allow it to be solved for the MAP estimate. As described in [8], computation of the SMM and subsequent MAP estimation is performed in the leading principal component subspace of the LR hyperspectral image. The components in the trailing subspace are interpolated onto the HR spatial grid by nearest neighbor or bilinear methods. Hence it realize spatial enhancement beyond the principal component subspace while reserving spectral information of LR hyperspectral image.

3.3.3. Estimation of Z without Specific Knowledge of PSF

In the term of enhancement of CE-I hyperspectral data, of which the PSF (H matrix in (5)) is unknown, ordinary de-convolution process cannot perform. Hereby two optimization algorithms for MAP estimation for Z in equation (5) without specific knowledge of PSF are introduced.

(a). An iterative conjugate gradient search algorithm can be used here to optimize the MAP estimation, as

$$\hat{z}^{(l+1)} = \hat{z}^{(l)} + \varepsilon v^{(l)} \tag{8}$$

where correction steps ε is obtained by minimizing(4). For each iteration, it is only necessary to retain the search direction v and inner product of the gradient from the prior iteration to perform Gram-Schmidt orthogonalization method to get the optimized estimation $\hat{z}$.

(b). Poisson optimization algorithm [10], developed in frequency domain on the basis of MAP estimation, can also be applied in the case of unknown PSF. It assumes that

$$\hat{z}^{n+1} = \hat{z}^{n} \exp\left[\left(\frac{x}{\hat{z}^{n} * h} - 1\right) * h\right] \tag{9}$$

where h is the PSF function, z^n is the nth iteration of the estimate of enhanced imagery. The sign * represents the convolution process. Without specific knowledge of PSF, Possion MAP iterates at each band of the hyperspectral imageries, it accelerates the computation of MAP enhancement. After the resolution has been enhanced, high frequency emphasis filtering is applied to process edge intensifying. The mask applied as

$$\begin{bmatrix} -1/9 & -1/9 & -1/9 \\ -1/9 & 17/9 & -1/9 \\ -1/9 & -1/9 & -1/9 \end{bmatrix} \tag{10}$$

4. EXPERIMENT RESULTS

4.1. Test Data

A hyperspectral image set obtained on 7/22/2008, and an auxiliary CCD image obtained on 1/26/2008, W29.5219 ~ E75.9045, S88.3598 ~ N87.9388, were selected as testing images.

4.2. Registration Results of Test Data

Fig.2 represents the implementation of region-based SIFT registration. First the interested regions are collected as denoted in red lines, then a number of SIFT feature points are further extracted as denoted in red labels to registrate the images by matching these feature points. Fig.3 represents the registration results applied on HR CCD and LR hyperspectral imageries.

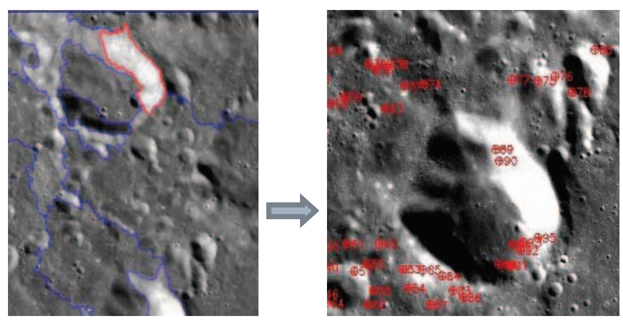
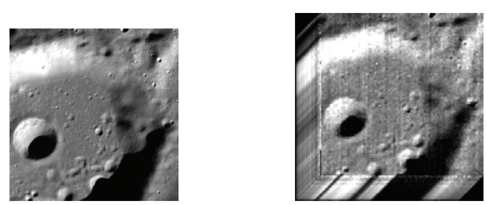


Fig.2 Implementation of region based SIFT algorithm.

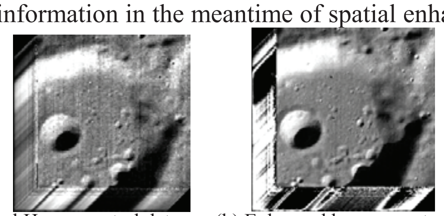


(a) Registrated CCD image (b) Registrated Hyperspectral data

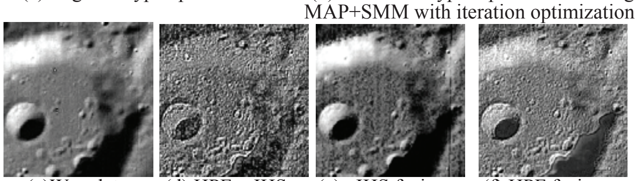
Fig.3 Testing results of applied Region based SIFT algorithm.

4.3. Results of Resolution Enhancement

The resolution enhanced hyperspectral data using MAP estimation with iterative optimization method is shown in Fig.4 (e), and the results of Possion optimization MAP method (Section 2.3.3) are shown in Fig.5. Some other resolution enhancing methods, including high-pass filter method, HIS transform methods, and wavelet analysis, are applied here to compare with the proposed methods. As displayed in Fig.4 (a) ~ (d), IHS fusion highlight the edge information, Wavelet method underlines the texture information and HPF smoothes the hyperspectral images. However, the experimental results show that the proposed MAP with SMM method with iteration optimization and Possion MAP are better than those methods in preserving spectral information in the meantime of spatial enhancement.

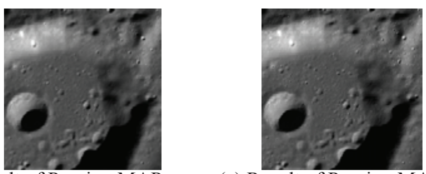


(a)Original Hyperspectral data (b) Enhanced hyper-spectral data using MAP+SMM with iteration optimization



(c)Wavelet (d) HPF + IHS (e) IHS fusion (f) HPF fusion

Fig.4 Different Resolution enhancement results



(b)Result of Possion MAP (c) Result of Possion MAP after high frequency data emphasis filtering

Fig.5 Possion optimization MAP resolution enhancement results

Standard deviation, information entropy and spectral degree twist are used to evaluate the performance of proposed method and several typical fusion methods on resolution enhancement of hyperspectral data. The results in Table.2 show the effectiveness of the proposed MAP method and Possion optimization method in both aspects of spatial resolution and spectra reservation.

TABLE.2. EVALUATION OF ENHANCING AND FUSION EFFECT

Object	Mean	Standard deviation	Information Entropy	Spectral twist degree* e-006
Original hyperspectral	0.0462821	0.0209272	6.16528	NA
HPF	0.0920066	0.0346792	7.08147	1.99951
HIS	0.0302125	0.0200889	9.41857	8.62971
HPF+HIS	0.0429727	0.0308653	9.78572	1.34406
Wavelet	0.048494	0.030046	8.04520	1.70642
MAP	0.0429727	0.040542	7.48400	0.87623
Possion MAP	0.0377533	0.0198524	6.82804	1.6056
Possion MAP + HF	0.0376861	0.0202472	6.83127	1.9339

The sharpened vision, the richened information entropy and lessened deviation illustrate that improved Possion MAP method has a desirable high resolution and visual quality and it tradeoffs between noise removal and preserving of image details. But it is obviously not quite as good in spectral twist degree and Information Entropy as MAP estimation with iterative optimization method.

5. CONCLUSION

This paper introduces an integrated method to enhance the resolution of hyperspectral data on CE-I using HR CCD image. First, a high-accuracy image registration method of Region based SIFT is applied to obtain aligned images. Then, the registered images are fused by MAP estimation combined with SMM. For the condition of unknown PSF, iteration optimization and Possion optimization methods are applied. Through a set of experiments, it is demonstrated that together with information from HR CCD sensor, the proposed method is more effective compared with other conventional methods in practice of spatial resolution enhancement for CE-1 hyperspectral data while reserving spectral information.

5. REFERENCES

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