MULTIRESOLUTION FUSION IN REMOTELY SENSED IMAGES: USE OF GIBBS PRIOR AND PSO OPTIMIZATION

Manjunath Joshi, Prakash Gajjar

DA-IICT, Gandhinagar, Gujarat, India.
{prakash_gajjar,mv_joshi}@daiict.ac.in

S. Ravishankar, K. V. V. Murty

Amrita School of Engineering, Banglore, India.
{s_ravishankar,kvv_murthy}@blr.amrita.edu

1. ABSTRACT

In this paper, we propose a model based approach for multi-resolution fusion of remotely sensed images. We obtain a high spatial resolution (HR) and high spectral resolution multi-spectral (MS) image using a high spatial resolution Panchromatic (Pan) image and a low spatial resolution (LR) MS image. This problem is ill-posed since we need to predict the missing high resolution pixels in each of the MS images and requires proper regularization in order to get better solution. Each of the low spatial resolution MS images is modeled as aliased and noisy versions of the corresponding fused HR image. The decimation matrix entries are estimated using the Pan data and the MS image. The prior for regularization is obtained by modeling the texture of the HR MS image as a Markov random field (MRF) that can be expressed as a joint probability density function (PDF) using the Gibbs distribution (GD). In our work we make inference about this joint PDF by using the available high spatial resolution Pan image. As proposed in [1] a set of filters is chosen from a filter bank to obtain the estimates of the marginal distributions of the GD as the histograms of the filtered outputs. Our final cost function consists of a data fitting term and a prior term which is then minimized to obtain the high spatial and spectral resolution MS image. The process is repeated for each of the MS images. The optimization is done using Particle swarm optimization (PSO) which can be implemented in parallel mode in order to reduce the time complexity. The main advantages of our approach are: 1) It requires no registration between Pan and MS images; 2) The spectral distortion is minimum as we are not using the actual Pan digital numbers; 3) The method can be applied to the fusion of Pan and MS images captured at different times and using different sensors. The drawback of the proposed method is its time complexity as one cannot use fast optimization approaches for minimization. However, we have attempted to reduce the computational complexity by using PSO. We demonstrate the effectiveness of our approach by conducting experiments on real satellite data captured by Quickbird satellite.

2. INTRODUCTION

Multi-resolution fusion is a method of combining a high spatial resolution Pan image and a low spatial but high spectral resolution MS image in order to obtain a high spatial and spectral resolution MS image [2]. Due to the physical constraint involving a trade-off between spatial and spectral resolutions, a great amount of research is being carried out in this field. Several approaches have been proposed to address the problem of multi-resolution fusion for remote-sensing applications. Most common methods include Intensity-hue-saturation (IHS) transform technique [3] and High-pass filtering (HPF) technique [4]. There are also approaches based on principal component analysis and wavelet transform (WT) technique [5]. More recent works on the multiresolution fusion can be found in [6][7][8]. Recently the authors in [9] proposed a model based approach for multiresolution fusion. Here the authors used a homogeneous autoregressive (AR) model as a prior. A non-homogeneous AR model based approach was proposed in [10] and the model parameters extracted from the Pan image were used in a regularization frame work to obtain the fusion. Our approach in this paper differs from these and the recent model based method proposed in [8]. We model each of the high resolution MS images as a separate GD and the marginal distributions for

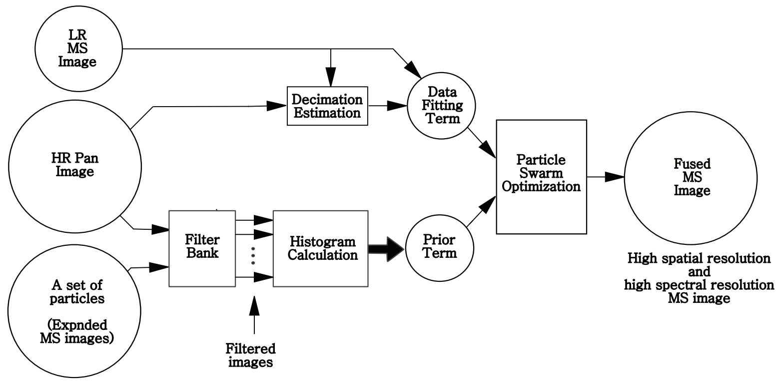

Fig. 1. Block diagram of multiresolution fusion process for a MS and PAN image. Here LR and HR correspond to low resolution and high resolution, respectively.

the same are obtained using the available Pan data. The number of marginal distributions is equal to the number of filters used (see [1]). The advantage of our method when compared to model based fusion methods is that the high resolution MS texture is better captured since we estimate it in the form of marginal distributions (histograms) from the available Pan image. Under the assumption that the same marginal distributions hold for the HR MS images, we enhance the spatial resolution of the MS images by using proper regularization. The basic assumption is that due to the similarity of the texture of each MS band with Pan data, the same distribution can be used in all the MS bands.

3. BLOCK DIAGRAM DESCRIPTION OF THE PROPOSED APPROACH

The proposed method for multi-resolution fusion is illustrated by the scheme shown in Fig.1. The block diagram illustrates the fusion process for the n^{th} low resolution MS image and the Pan image giving the fused MS image as the result. A simple least squares approach is used to estimate the decimation [11] using the MS and Pan data. The marginal distribution prior is obtained by passing the Pan image through different filters and computing the histograms of the filtered outputs. Laplacian of Gaussian (LOG) and Gobor filters with different parameters are selected as filters and there are N filtered outputs. We then enhance the spatial resolution of the MS image by using a proper regularization which has a data fitting term and prior (histogram matching) term. In other words we try to find the fused image which matches the model for image formation (data fitting term) and also incorporates the texture characteristics of the high resolution Pan image expressed in terms of the marginal distribution (prior term). The final cost function to obtain the estimate of the fused image as $\hat{\mathbf{z}_n}$ can be expressed as

$$\hat{\mathbf{z}}_n = \underset{z}{argmin} \left[\frac{\| \mathbf{y}_n - D\mathbf{z}_n \|^2}{2\sigma_n^2} + \lambda \sum_{\alpha=1}^{N} |H_z^{(\alpha)} - H_{z_n}^{(\alpha)}| \right], \tag{1}$$

where λ is a suitable weight for the regularization term. Here $\mathbf{y}$ and $\mathbf{z}_n$ represent the lexicographically ordered n^{th} observed MS image and the corresponding fused MS image (to be estimated), respectively. $H_z^{(\alpha)}$ and $H_{z_n}^{(\alpha)}$ are the histograms of the Pan image and the fused MS image random fields, respectively. D represents the decimation matrix and σ_n^2 is the noise variance. It may be mentioned here that we are not discussing on the choice and the proper number of filters required for representing the joint density. The above cost function has intensity term and a histogram term and hence cannot be minimized using simple optimization method based on gradients. We use particle swarm optimization (PSO) for minimization where one can use parallel computations to reduce the time complexity. This avoids the use of costly optimization methods such as simulated annealing. The minimization is carried out for each of the MS images to obtain the fused MS images.

4. PARTICLE SWARM OPTIMIZATION

In order to speed up the convergence and reduce the computation time we propose the use of particle swarm optimization (PSO) technique. Recently, researchers have explored the use of PSO to solve variety of problems in image processing and pattern

(a) (b) (c) (d) (e)

Fig. 2. Fusion results on a degraded MS image of Quickbird satellite. (a) 128×128 true MS image, (b) Decimated and noisy version of (a). (c) Fused image using HPF approach (d) Expanded MS image using bicubic interpolation (e) Fused image using the proposed approach.

recognition [12]. PSO is initialized with a group of particles and the algorithm then searches for the best solution through an iterative process by computing the fitness (cost). If it is the best value the particle has achieved so far, the particle stores that value as 'personal best'. The best fitness value achieved by any particle during current iteration is stored as 'global best'. Let $S = \{Z_b^{k+1} | b = 1, 2, \ldots, B\}$ be a swarm initialized with initial HR MS images as the particles. Let Z_{bp}^k and Z_g^k be the personal and the global best particles, respectively at the k^{th} iteration with the fitness values as $F_{Z_{bp}^k}$ and $F_{Z_g^k}$, respectively. While using the PSO the velocity V_b and position Z_b after k^{th} iteration are updated according to the following two equations

$$\begin{aligned} V_b^{k+1} &= wV_b^k + c_1 r_1 (F_{Z_{bp}^k} - F_{Z_b}^k) + c_2 r_2 (F_{Z_g^k} - F_{Z_b}^k), \\ Z_b^{k+1} &= Z_b^k + V_b^k, \end{aligned}$$

where w is weighting function, r_1 and r_2 are the random numbers uniformly distributed in $[0, 1]$, c_1 and c_2 are cognitive and social parameters, respectively. The minimization leads to Z_n, i.e., the n^{th} fused MS image.

5. EXPERIMENTAL RESULTS

The experiments are conducted on a simulated data captured from the Quickbird satellite. The Quickbird data set consists of four MS bands at a spatial resolution of 2.4 m $\times$ 2.4 m and a Pan image with a spatial resolution of 0.6 m $\times$ 0.6m (giving a spatial resolution difference or decimation factor of 4). In the experiment we use MS images and the Pan image captured over the Malpensa area, Italy. The filters used to estimate marginal distribution are selected selected. Fig.2(a) shows the ground truth MS image. A decimated and noisy version of the same, shown in Fig.2(b), is used as a test image. Fig.2(c) shows the fused image using HPF method, while Fig.2(d) shows the expanded MS image using bicubic interpolation. The fused image obtained using the proposed approach is shown in Fig.2(e). The comparison with bicubic interpolation shows that the proposed method performs better in terms of perceptual quality of images. We are conducting the experiment for selecting the best set of filters so that the texture of the image is captured effectively. With the use of the best set of filters, the proposed approach can yield better results as compared to the existing methods (HPF approach) for fusion.

6. CONCLUSION

We have proposed a novel technique for multiresolution fusion of remotely sensed images. Our approach differs from other model based approaches in the choice of prior for regularization purposes. The prior information is obtained by modeling the texture of the HR MS image as a Gibbs distribution and the marginals of this joint distribution are obtained as the histograms of the filtered outputs with the input as the Pan image. The final cost function is minimized using particle swarm optimization which can be implemented in parallel mode in order to reduce the time complexity. The experimental results show that the proposed approach yields better results.

7. REFERENCES

[1] S. C. Zhu, Y. Wu., and D. Mumford, "Filters, random fields and maximum entropy (frame): Towards a unified theory for texture modeling," *International Journal on Computer Vision*, vol. 27, no. 2, pp. 107–126, March 1998.

[2] L. Wald, "Some terms of reference in data fusion," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, no. 3, pp. 1190–1193, 1999.

[3] M. Choi, "A new intensity-hue-saturation fusion approach to image fusion with a tradeoff parameter," *IEEE Trans. Geosci. Remote Sensing*, vol. 44, no. 6, pp. 1672–1682, June 2006.

[4] P. S. Jr. Chavez, S. C. Sides, and J. A. Anderson, "Comparison of three different methods to merge multiresolution and multispectral data: Landsat tm and spot panchromatic," *Photogrammetric Engineering and Remote Sensing*, vol. 57, no. 3, pp. 295–303, 1991.

[5] H. Li, B. S. Manjunath, and S. K. Mitra, "Multisensor image fusion using the wavelet transform," *Graphical Models and Image Processing*, vol. 27, no. 3, pp. 235–244, 1995.

[6] M. V. Joshi and A. Jalobeanu, "Multiresolution fusion in remotely sensed images using an IGMRF prior and MAP estimation," in *IEEE Int. Geoscince and Remote Sensing Symposium*, Boston MA, USA, July, 2008, pp. 269–272.

[7] D. Fasbender, J. Radoux, and P. Bogaert, "Bayesian data fusion for adaptable image pansharpening," *IEEE trans. on Geoscience and remote sensing*, vol. 46, no. 6, pp. 1847–1857, June 2008.

[8] H. Aanaes, J. R. Sveinsson, A. A. Nielsen, T. Bϕvith, and J. A. Benediktsson, "Model based satellite image fusion," *IEEE trans. on Geoscience and remote sensing*, vol. 45, no. 5, pp. 1336–1346, May 2008.

[9] Lorenzo Bruzzone Manjunath V. Joshi and Subhasis Chaudhuri, "A model-based approach to multiresolution fusion," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, pp. 177–192, September 2006.

[10] Krishna Rudraraju and Manjunath Joshi, "Nonhomogeneous autoregressive model based prior for multiresolution fusion," in *IEEE Int. Geoscince and Remote Sensing Symposium*, Capetown, South Africa, July, 2009.

[11] P. P. Gajjar, M. V. Joshi, A. Banerjee, and S. Mitra, "Decimation estimation and super-resolution using zoomed observations," in *Proc. Indian conf. Computer Vision Graphics and Image Processing*, 2006, pp. 45–57.

[12] M. G. H. Omran, *PSO methods for pattern recognition and image processing*, Ph.D. thesis, Pretoria University, Nov 2004.