MAP-MRF ESTIMATION FOR MULTIRESOLUTION FUSION OF REMOTELY SENSED IMAGES

Manjunath Joshi, Abhishek Shripat, Pradipta Nanda

S. Ravishankar, K. V. V. Murthy

DA-IICT, Gandhinagar, Gujarat, India.
Institute of Technical Education & Research,
Bhubaneswar, India.

Amrita School of Engineering,
Banglore,
India.

1. ABSTRACT

In this paper we propose a model based approach for multiresolution fusion for the satellite images. Given a high resolution panchromatic (Pan) image and a low spatial but high spectral resolution multi spectral (MS) image acquired over the same geographical area, the objective is to obtain a high spatial resolution MS image. To solve this problem use a *maximum a posteriori* (MAP) - Markov random field (MRF) based approach. Each of the low spatial resolution MS images are modeled as the aliased and noisy versions of their high resolution versions. The high spatial resolution MS images to be estimated are modeled separately as discontinuity preserving MRF that serve as a prior information. The MRF parameters are estimated from the available high resolution Pan image using homotopy continuation method. The proposed approach has the advantage of having minimum spectral distortion in the fused image as we do not directly operate on the Pan digital numbers. Our method do not require registration of MS and Pan images. Also the number of MRF parameters to be estimated from the Pan image are limited as we use homogeneous MRF. The time complexity of our approach is reduced by using the particle swarm optimization (PSO) in order to minimize the final cost function. We demonstrate the effectiveness of our approach by conducting experiments on real image captured by Landsat-7 ETM+ satellite.

2. INTRODUCTION AND PROBLEM STATEMENT

Multiresolution fusion is the process of combining data from high spatial resolution panchromatic (Pan) image and low spatial but high spectral resolution multispectral (MS) image to obtain high spatial as well as high spectral resolution image [1]. Due to the hardware limitations in achieving an acceptable signal to noise ratio, there arise a need for multiresolution fusion that enhances the spatial resolution of MS images using image processing techniques [2][3][4][5]. Most of the multiresolution fusion approaches use the upsampling of MS image through standard interpolation techniques that do not take care of aliasing present in the low resolution MS observations and hence causes distortion in the fused image. At the same time most of the approaches use Pan pixel values directly for the purpose of fusion, which may be a practical constraint affecting the fusion result when the Pan and MS images are acquired by different satellites. Authors in [6][7][8] proposed the model based approaches for fusion which do not operate directly on the Pan pixels, instead learn the spatial correlation from the available Pan image. The disadvantage of the approach proposed in [6] is that the spatial dependency is not well captured due to the use of a linear model and the use of limited number of parameters. Better capture of the spatial dependency requires a larger number of parameters which increases the computational complexity. In [7] although MRF is used as a prior there is a need for registration since it is inhomogeneous. Also the computational complexity is high since the parameters are estimated for every pixel. Registration is

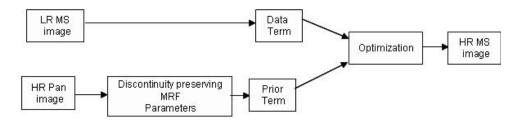


Fig. 1. Block diagram of multiresolution fusion process for a MS and PAN image. Here LR and HR correspond to low resolution and high resolution, respectively.

required for the method proposed in [8] which also use the high resolution estimate derived from the Pan image. In this paper we solve the multiresolution problem using a discontinuity preserving homogeneous MRF model and hence we do not require the registration between the MS and Pan images. The spectral distortion is minimum since we are not directly operating on the Pan pixels. The high frequency details are better preserved and the distortion due to aliasing is minimized with help of the estimated decimation matrix.

3. BLOCK DIAGRAM DESCRIPTION OF THE PROPOSED METHOD AND EXPERIMENTS

The block diagram in Figure 1 illustrates the proposed fusion process for a k^{th} low resolution MS image. A low resolution MS image is modeled as the decimated and noisy version of the high resolution MS image. This is used to constitute the data term. The discontinuity preserving MRF parameters estimated using the Pan image are used in the prior term. In our case we estimate two parameters (μ and γ) for the entire image. The final cost function derived using the MAP-MRF formulation consists of data term and prior term which can be expressed as follows

$$\epsilon = \frac{argmin}{z} \left[\frac{\parallel \mathbf{y} - D\mathbf{z}_k \parallel^2}{2\sigma^2} + U(\mathbf{z}_k, \mathbf{l}_k, \mathbf{v}_k) \right], \tag{1}$$

Here \mathbf{y} and \mathbf{z}_k represent the lexicographically ordered k^{th} observed MS image and the corresponding fused MS image (to be estimated), respectively. D represents the decimation matrix and σ^2 is the noise variance. $U(\mathbf{z}_k, \mathbf{l}_k, \mathbf{v}_k)$ is the energy function and arises due to MRF equivalence with Gibbs distribution. This is expressed as follows [9]

$$U(\mathbf{z}_{k}, \mathbf{l}_{k}, \mathbf{v}_{k}) = \sum_{i,j} \mu[(z_{k}(i,j) - z_{k}(i-1,j))^{2} (1 - l_{k}(i,j))$$

$$+ (z_{k}(i+1,j) - z_{k}(i,j))^{2} (1 - l_{k}(i+1,j))$$

$$+ (z_{k}(i,j) - z_{k}(i,j-1))^{2} (1 - v_{k}(i,j))$$

$$+ (z_{k}(i,j) - z_{k}(i,j+1))^{2} (1 - l_{k}(i,j+1))]$$

$$+ \gamma[l_{k}(i,j) + l_{k}(i+1,j) + v_{k}(i,j) + v_{k}(i,j+1)]$$
(2)

Where μ and γ are the MRF parameters estimated from the Pan image using homotopy continuation method [10]. Here \mathbf{z}_k is the high resolution MS image and \mathbf{l} and \mathbf{v} are horizontal and vertical line fields. Since we are using discontinuity preserving MRF prior the cost function becomes non convex and hence cannot be minimized using simple optimization techniques like gradient descent. We use particle swarm optimization (PSO) technique to minimize the same and obtain the estimate of the fused image. The advantage of our approach is that we do not require computationally taxing optimization method such as simulated annealing as we can implement PSO using parallel mode. This results in quick convergence. The optimization is

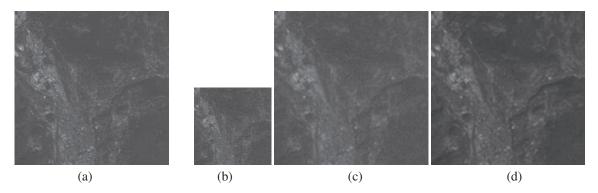


Fig. 2. Fusion results on a degraded band-1 MS image of Landsat-7 ETM+ satellite. (a) 256×256 true MS image. (b) Decimated and noisy version of (a). (c) Fused image using HPF approach. (d) Fused image using the proposed approach.

carried out separately for each of the MS images thus obtaining a fused image for each of the MS bands. Figure 2 shows the results of fusion on band-1 of Landsat-7 ETM+ satellite image and compared with HPF approach [3]. The proposed method performs better in terms of perceptual quality as depicted in the high lighted region. It can be clearly seen that the details are more clear in the fused image using our approach. We have observed that the proposed method performs better in terms of quantitative measures as well.

4. CONCLUSION

By modeling the high resolution MS image as discontinuity preserving homogeneous MRF and estimating the MRF parameters from the Pan image through homotopy continuation method we have avoided the direct use of Pan pixels for fusion. This also avoids the need for registering the MS and Pan data. The use of PSO optimization reduces the computational complexity as the algorithm converges faster with the use of parallel implementation.

5. REFERENCES

- [1] L. Wald, "Some terms of reference in data fusion," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, no. 3, pp. 1190–1193, 1999.
- [2] R. Hayden, G. W. J. Henkel, and J. E. Bare, "Application of the ihs color transform to the processing of multisensor data and image enhancement," in *Proc. International Symposium on Remote sensing of arid and semi-arid lands*, Cairo, Egypt, 1982, pp. 599–616.
- [3] Chavez P. S. Jr., 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.
- [4] E. Yu and R. Wang, "Fusion and enhancement of the multispectral image with wavelet transform," *Computer Engineering and Science*, vol. 23, no. 1, pp. 47–50, 2001.
- [5] M. Gonzàlez, A. Audicana, J. L Saleta, R. Garcia Catalàn, and R. Garcia, "Fusion of multispectral and panchromatic images using improved IHS and PCA mergers based on wavelet decomposition," *IEEE Trans. Geosci. Remote Sensing*, vol. 42, no. 6, pp. 1291–1299, June 2004.
- [6] Manjunath V. Joshi, Lorenzo Bruzzone, and Subhasis Chaudhuri, "A model-based approach to multiresolution fusion," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, pp. 177–192, September 2006.

- [7] 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.
- [8] H. Aanaes, J. R. Sveinsson, A. A. Nielsen, T. B ϕ vith, 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] S. Geman and D. Geman, "Stochastic relaxation, gibbs distribution and the bayesian restoration of images," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 6, pp. 721–741, November 1984.
- [10] Nanda P. K., Desai U. B., and Poonacha P.G, "Joint parameter estmation and restoration using mrf models and homotopy continuation method," *ISCAS*, pp. 273–276, 1994.