http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 7 (7): 1030-1036, 2008
ISSN 1812-5638

Super-Resolution Challenges in Hyperspectral Imagery

[1]Fereidoun A. Mianji, [1]Ye Zhang, [1]Humayun Karim Sulehria,
[2]Asad Babakhani and [2]Mohammad Reza Kardan
[1]Institute of Image and Information Technology,
Harbin Institute of Technology, 150001, People's Republic of China
[2]NRPD, Iran National Regulatory Authority, Iran

Abstract: In this study, a variety of recent proposed spatial and spectral processing methods for hyperspectral imagery is reviewed and several important aspects of super-resolution problems and challenges are presented. The inherent variability in target and background spectra in hyperspectral imagery, the problem of high dimensionality of hyperspectral data in hyperspectral image classification, limitation in application of learning-based methods and the question of an optimal resolution factor for an arbitrary set of images, are some of the main challenges in this field.

Key words: Hyperspectral imagery, super-resolution, spatial processing, spectral processing, image classification, learning-based method

INTRODUCTION

In most electronic imaging applications, High Resolution (HR) is required. An HR image can offer more details than a Low Resolution (LR) image due to its higher pixel density and which is more crucial in various applications. Spatial resolution is the basis for expressing the resolution of monochrome images, while for a color images or material analysis purposes, spectral resolution must be seriously taken into account.

Many applications involve the remote detection of objects such as the species of plants on the ground or military vehicles. For this kind of applications hyperspectral imagery is more adequate. Figure 1 shows how hyperspectral imagery sensors provide image data containing both spatial and spectral information. The basic idea for hyperspectral imaging stems from the fact that, for any given material, the amount of radiation that is reflected, absorbed, or emitted, i.e., the radiance, varies with wavelength. Hyperspectral imaging sensors measure

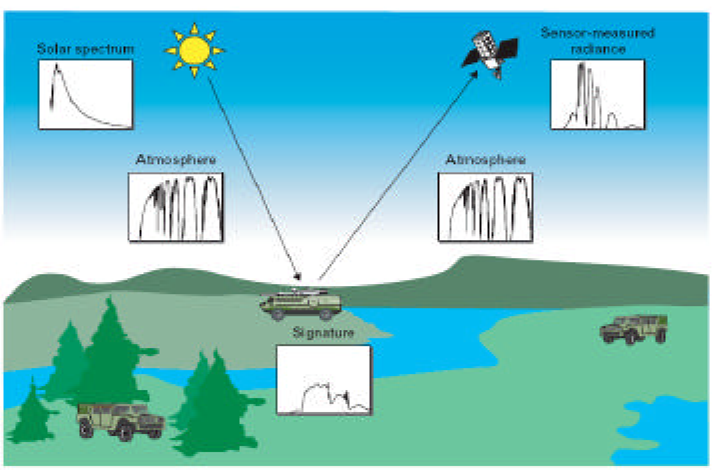

Fig. 1: Four basic parts of a remote sensing system: the radiation source, the atmospheric path, the imaged surface and the sensor

Corresponding Author: Fereidoun A. Mianji, Institute of Image and Information Technology, Harbin Institute of Technology, 150001, People's Republic of China

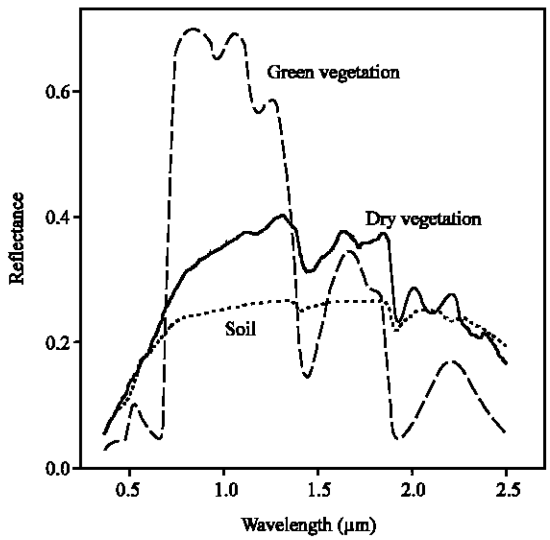

Fig. 2: Different materials produce different electromagnetic radiation spectra. The spectral information contained in a hyperspectral image pixel can therefore indicate the various materials present in a scene

the radiance of the materials within each pixel area at a very large number of contiguous spectral wavelength bands (Manolakis *et al*., 2003). The resulting reflectance representation, termed the spectral signature, if sufficiently characterized, can be used to identify specific materials in a scene.

Figure 2, for example, illustrates the different reflectance spectra for naturally occurring materials such as soil, green vegetation and dry vegetation.

Unfortunately, atmospheric scattering, secondary illumination, changing viewing angles and physical limitations of imaging sensors such as dynamic range, pixel size, artifacts and sensor noise degrade the quality of these data. We refer to the hyperspectral remote sensing system shown in Fig. 1 again, to describe the process. It has four basic parts including the radiation source, the atmospheric path, the imaged surface and the sensor. The primary source of illumination in a passive remote sensing system is the sun. The solar energy is modified before reaching the sensor due to the following factors:

- Intensity modifications and spectral changes during propagation through the atmosphere.
- Interaction with the imaged surface materials and reflection, transition and/or absorption by these materials.
- Additional intensity modifications and spectral changes during passing back through the atmosphere.

Finally, the energy reaches the sensor, where it is measured and converted into digital form for further processing and exploitation.

Spatial resolution enhancement and spectral resolution enhancement are basically different approaches for different applications, but the need for both spatial and spectral resolution in many hyperspectral images has attracted many researchers to develop new techniques for super-resolution of hyperspectral imagery in both spatial and spectral regions. In this research, some areas of research in Super-Resolution (SR) of hyperspectral imagery are outlined and some of the effective methods in resolution enhancement and the main challenges in this field are highlighted. It is also shown that despite the lower relevance of spatial resolution in hyperspectral imagery it is of a considerable importance in it.

SPECTRAL RESPONSE OF END MEMBERS

A frequent assumption in hyperspectral remote sensing is that spectral signatures result from linear combinations of end-member spectra (Penn, 2002). End-member spectra are end-member components in n-dimensional space. Let E equal the number of end-members in the spectral library with e ranging from 1 to E. Each spectrum in the library consists of N discrete wavelengths (λ_n) where n = 1 to N. Let $S^e(\lambda_n)$ represent the spectral response of material e at wavelength λ_n. Each spectrum in the library is described by the following vector:

$$S^e = (S^e(\lambda_1), S^e(\lambda_2), ..., S^e(\lambda_N)) \quad (1)$$

For an unknown spectra $u = (u_1, u_2, ..., u_N)$ each vector component is composed of a linear combination of m end-members from M. u is related to M by the estimation vector $x = (x_1, x_2, ..., x_E)$ where, $0 \le x_e \le 1$ and $\sum_{e=1}^{E} x_e = 1$. For a mixture described by u, the spectral response at λ_n, $S^u(\lambda_n)$, would be as following:

$$S^u(\lambda_n) = \sum_e x_e S^e_{\lambda_n} \quad (2)$$

DATA CUBES AND MIXED PIXELS

Airborne hyperspectral imaging sensors produce a three dimensional (3D) data structure (as a result of spatial and spectral sampling), referred to as a data cube.

Figure 3 shows an example of such a data cube. If we extract all pixels in the same spatial location and plot their spectral values as a function of wavelength, the result is the average spectrum of all the materials in the corresponding ground resolution cell. In contrast, the

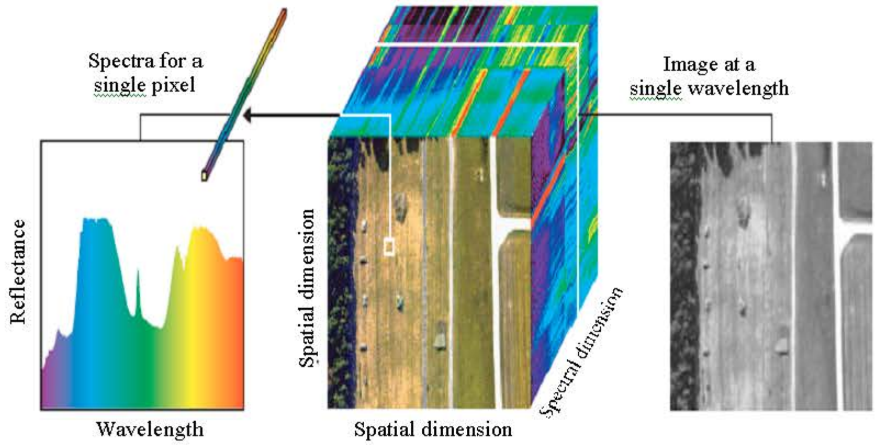

Fig. 3: Spectra for single pixels in hyperspectral images and spectral cube

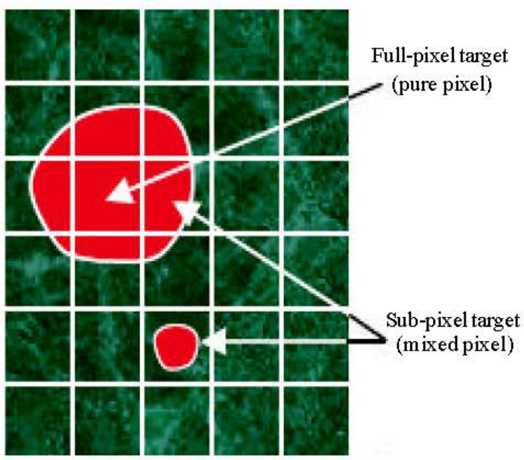

Fig. 4: Pure pixels and mixed pixels. Smaller targets are detectable by means of smaller pixel sizes

values of all pixels in the same spectral band, plotted in spatial coordinates, result in a grayscale image depicting the spatial distribution of the reflectance of the scene in the corresponding spectral wavelength (Manolakis *et al*., 2003). A hyperspectral data cube is composed of pure and mixed pixels, where a pure pixel contains a single surface material and a mixed pixel contains multiple materials. Figure 4 shows the mixed-pixel interference.

Figure 4 shows that how depending on the spatial resolution of the sensor and the spatial distribution of surface materials within each ground resolution cell, radiance from all materials within a ground resolution cell is seen by the sensor as a single image pixel. Mixed-pixel interference is one of the main obstacles in hyperspectral imagery.

SPATIAL PROCESSING VS. SPECTRAL PROCESSING

All practical sensors have limited spatial and spectral resolution, which results in finite-resolution recordings of the scene radiance. The field of digital image processing refers to processing digital images by means of a digital computer aiming for improvement in quality of LR images. The most direct solution to increase spatial resolution is to reduce the pixel size (the basic unit of image sensor). As the pixel size decreases, however, shot noise that degrades the image quality increases. To avoid the severe effects of shot noise, there is a limitation on the pixel size reduction; the optimally limited pixel size is about 40 μm^2 for a 0.35 μm CMOS process (Choi *et al*., 2004). Due to the fact that current image sensor technology has almost reached this level, the best approach is to use image processing methods to obtain a HR image from observed low resolution images. Basic methods for image enhancement include:

- Enhancement in Spatial Domain (SD) using techniques such as histogram processing, arithmetic/ logic operations and spatial filtering.
- Enhancement in Frequency Domain (FD) using Smoothing FD Filters, Sharpening FD Filters and Homomorphic Filtering.

Spatial methods have proven to be more flexible and efficient compared to the frequency methods (Omrane and Palmer, 2003). SR algorithms attempt to extract the high-resolution image corrupted by the limitations of the optical imaging system. This type of problem is an example of an inverse problem, wherein the source of

Table 1: Comparison of spatial processing and spectral processing

Spatial processing	Spectral/hyperspectral processing
Spatial arrangement of pixels is the information	Materials can be identified by the associated spectrum of pixels
Better shape recognition needs higher spatial resolution	High spatial resolution is not of crucial importance
Data volume increases with the square of the spatial resolution	Data volume increases linearly with the number of spectral bands
Fully automated algorithms are not feasible	Fully automated algorithms are available for some applications
Multiframe color algorithms are much more difficult than that of monochrome imaging	No. of bands just increases the necessary processing time
It exploits geometrical shape information	It exploits geometrical shape information and material recognition
The main challenge is the pixel size	The main challenge is spectral variability

information (high-resolution image) is estimated from the observed data (low-resolution image or images) (Farsiu *et al*., 2004).

The spectral resolution is determined by the width $\Delta\lambda$ of the spectral bands used to measure the radiance at different wavelengths λ. In Table 1 (adapted from Manolakis *et al*., 2003) some of the most important properties of spatial and spectral image processing are compared. Generally, speaking hyperspectral processing techniques are of higher priority in remote sensing although, it should be noticed that higher spatial resolution is desired even in hyperspectral imagery.

Any effort to measure the spectral properties of a material through the atmosphere must consider the absorption and scattering of the atmosphere, the subtle effects of illumination and the spectral response of the sensor. The recovery of the reflectance spectrum of each pixel from the observed radiance spectrum is facilitated with the use of sophisticated atmospheric compensation codes. Now we discuss the main approaches for SR as applied to hyperspectral imagery.

MAIN APPROACHES TO SUPER-RESOLUTION

The SR problem has received much interest within the Image Processing (IP) community. Lu *et al.* (2004) suggested that the underlying meaning of the SR problem refers to super-resolving an imaging system by image sequence observation, instead of merely improving the image sequence itself. An SR algorithm consists of two steps: image registration and fusion of many LR images into an HR image. Many effective techniques have been developed for the first step, which is also called motion estimation (Chalidabhongse and Kuo, 1997; Li *et al*., 1994). The second step is based on the fact that the HR image, after being appropriately shifted, blurred and down-sampled to take into account the alignment and to model the imaging process, should produce the LR images.

Learning-Based Method (LBM): A general SR method is to capture multiple LR observations of the same scene by sub-pixel shift in the image sensor's motion. However, this method requires an accurate registration process, a difficult and challenging task (Joshi *et al*., 2006). In recent years, IP researchers have started to exploit different approaches to overcome this difficulty, as discussed here. One technique is the LBM for image SR, in which, a database of high-resolution training images is used to create high-frequency details in the zoomed images (Baker and Kanade, 2002; Capel and Zisserman, 2001; Freeman *et al*., 2002). The main advantage of LBM is that it provides a natural way of obtaining the required image characteristics. The main disadvantage of this method is requiring a long learning time that severely limits its applications.

Reconstruction-Based Algorithms (RBA): These algorithms have been around for a few decades and produce HR images that minimize the difference between observed LR images and images estimated from the HR image with a camera model. There are some techniques and problems for RBA and these are explained below.

SR variable-pixel linear reconstruction: The development and applications of this SR method, is described in (Merino and Nunez, 2007). The algorithm works by combining different LR images in order to obtain, a resultant HR image. It is shown that it can make spatial resolution improvements to satellite images of the Earth's surface, allowing recognition of objects with sizes approaching the limiting spatial resolution of the LR images.

Blur and noise: Blur in LR images has received considerable attention in image reconstruction. In many practical situations, the blur is often unknown and little information is available about the true image. Therefore, the true image is identified directly from the corrupted image by using partial or no information about the blurring process and the true image. In overcoming the blur problem, blind SR techniques are used and it is anticipated that research in integrating various blind SR algorithms will continue in the future (Lu *et al*., 2004).

In addition, noise is often amplified that induces severely ringing or aliasing artifacts in the process of restoration (Pan, 2002). Some new methods for the reconstruction of a HR image from a set of highly undersampled and thus aliased images are presented in some articles (Marziliano and Vetterli, 2000; Vandewalle *et al*., 2004; Vandewalle *et al*., 2005).

Computational complexity: RBA requires iterative calculations and has large calculation costs because reconstruction-based SR is a large-scale problem (Tanaka and Okutomi, 2007). The proposed methods (Alvarez *et al*., 2004; Zhang *et al*., 2005) for solving the problem of computational complexity are to introduce fast algorithms, such as:

- Reducing the number of observed pixel value estimations from the high resolution image
- Using an average of pixel values in a divided region
- Determining the pixels in the image that provide useful information for calculating the HR image and
- Parallel image reconstruction

Other performance measures: All the suggested techniques have limited performance. SR performance depends on a complex relationship between measurement SNR, the number of observed frames, sets of relative motions between frames, image content and the imaging system's Point-Spread Function (PSF) (Robinson and Milanfar, 2006). It has been shown that this degradation occurs most severely along edges within images. Furthermore, the question of an optimal resolution factor for an arbitrary set of images is still intriguing (Farsiu *et al*., 2004).

Instrumental Schemes (IS): Instrumental limitations in hyperspectral (HS) cameras make it difficult to perform HR scanning of microscopic samples, target and material identification in remotely sensed data as well. Appreciating the significance of this problem, some IS and computational methods for improving the spatial resolution of HS images were proposed (Munechika *et al*., 1993; Robinson *et al*., 2000). As an example, the increase in scanning resolution of microscopic samples can be achieved by combining a high-precision stepping table which shifts the spatial positions of the HS camera with a maximum entropy SR method (Buttingsrud and Alsberg, 2006). The basis of this method is to combine multiple LR HS images to construct a single HS image with a higher spatial resolution at all wavelengths such that the spectral profiles in each pixel is accurate. The generated image quality is limited by the resolution and noise of the stepping table and the original camera.

Fusion methods: Improving the resolution in HS images has a high payoff, but applying SR techniques separately to each spectral band is problematic for two main reasons. First, the number of spectral bands can be in the hundreds, increasing the computational load excessively. Second, considering the bands separately does not make use of the information that is present across them. Furthermore, separate band SR does not make use of the inherent low dimensionality of the spectral data, which can effectively improve the robustness against noise. A proposed approach is a model that enables representing the HS observations from different wavelengths as weighted linear combinations of a small number of basis image planes (Bachmann *et al*., 2005). Then, a method for applying SR to HS images using this model is presented. The method fuses information from multiple observations and spectral bands to improve spatial resolution and reconstruct the spectrum of the observed scene as a combination of a small number of spectral basis functions.

Resolution in target and material identification in remotely sensed data may be enhanced by the use of spectral information (Rhody, 2002). The basis for this technique is the fact that HS instruments can gather high-resolution spectral information, but suffer from low spatial resolution. Conversely, monochrome or color images that have high spatial resolution have low spectral resolution. The fusion of the two types of images has been proposed to produce a data set that has higher resolution in both the spatial and spectral domains than that can be obtained either type of image alone.

Curvelet transform: An improved method of image fusion is based on the amélioration de la résolution spatiale par injection de structures (ARSIS) concept using the curvelet transform (Choi *et al*., 2005). Based on the fact that the curvelet transform represents edges better than wavelets and regarding the importance of edges in image representation, enhancing spatial resolution has been carried out by means of enhancing the edges.

MAP estimation method: Another approach is a maximum a posteriori (MAP) estimation method for enhancing the spatial resolution of an HS image using a higher resolution coincident panchromatic image (Eismann and Hardie, 2004). This involves the use of a stochastic mixing model of the underlying spectral scene content to optimize the estimated HS scene.

SVM classification approach: The SVM classification approach in fusion of HR and HS imagery is also an effective way to produce a data set that has higher resolution in both the spatial and spectral domains (Gualtieri and Chettri, 2000). Improving the classification accuracy using spectrally weighted kernels is also investigated by means of assigning weights to different bands according to the amount of useful information they contain (Guo *et al*., 2005).

Non-linear methods: Methods for exploiting the nonlinear structure of HS imagery were developed and compared against the *de facto* standard of linear mixing in a new algorithm (Bachmann *et al*., 2005). This approach seeks a manifold coordinate system that preserves geodesic distances in the high-dimensional HS data space. Algorithms for deriving manifold coordinates, such as isometric mapping (ISOMAP), have been developed for other applications. ISOMAP guarantees a globally optimal solution, but is practical only for small datasets because of computational and memory requirements.

Other methods: Optical and structural properties of images, such as 3-D shape of an object, regional homogeneity, local variations in scene reflectively, etc., are also of importance in HS imaging. Some techniques are proposed based on generalized interpolation and polarization for separation of real components from reflected components in an overlapping panchromatic image that is useful for many applications such as high quality TV camera images (Ohnishi *et al*., 1996; Rajan and Choudhuri, 2001; Schechner *et al*., 1999). The underlying theory for the application of anomaly detection to systems with inherently high dimensionality is outlined in (Stein *et al*., 2002). It is demonstrated that the performance improves with SNR and diminishes with increasing dimension.

Joint Endmember Determination (JEMD) is the technique used to combine a HR image with a low spatial resolution HS image to produce a product that has the spectral properties of the HS image at a spatial resolution approaching that of the panchromatic image (Winter and Winter, 2002).

CONCLUSIONS

Despite the considerable advances in SR of hyperspectral imagery, some important challenges still lie ahead in developing a SR algorithm capable of producing high-quality results on general image sequences. Spectral basis of hyperspectral imagery makes it a powerful tool in material analysis and target recognition but the increasing demand for higher spatial resolution in hyperspectral imagery makes it more challenging. Some of the main challenges in this field can be categorized as the follows:

- In spite of the emphasis of hyperspectral imagery on spectral information of the ground cells, many of the researches have focused on spatial resolution enhancement of hyperspectral imaging techniques.
- Computational complexity of SR algorithms is one of the major challenges which restrict us from achieving higher standards in image processing.
- Requiring a long learning time is the significant disadvantage of learning-based methods that severely limits their applications to SR problem. Learning-based methods are effective when applied to very specific scenarios, such as faces or text.
- Inherent variability in target and background spectra is a severe obstacle in development of effective detection algorithms for hyperspectral imagery. The use of adaptive algorithms deals quite effectively with the problem of unknown backgrounds; the lack of sufficient target data, however, makes the development and estimation of target variability models challenging.
- One of the main problems encountered with hyperspectral image classification is the high dimensionality of hyperspectral data; such as, the AVIRIS hyperspectral sensor has 224 spectral bands.

REFERENCES

Alvarez, L.D., J. Mateos, R. Molina and A.K. Katsaggelos, 2004. High-resolution images from compressed low-resolution video: Motion estimation and observable pixels. Int. J. Image. Syst. Technol., 14: 58-66.

Bachmann, C.M., T.L. Ainsworth and R.A. Fusina, 2005. Exploiting manifold geometry in hyperspectral imagery. IEEE Trans. Geosci. Remote Sensing, 43: 441-454.

Baker, S. and T. Kanade, 2002. Limits on super-resolution and how to break them. IEEE Trans. Pattern Anal. Mach. Int., 24: 1167-1183.

Buttingsrud, B. and B.K. Alsberg, 2006. Super-resolution of hyperspectral images. Chemometrics Intell. Lab. Syst., 84: 62-68.

Capel, D. and A. Zisserman, 2001. Super-resolution from multiple views using learnt image models. Proc. IEEE Comp. Soc. Conf. Comp. Vis. Pattern Recogn., CVPR'01: 627-634.

Chalidabhongse, J. and C.C.J. Kuo, 1997. Fast motion vector estimation using multiresolution-spatio-temporal correlation. IEEE Trans. Circuits Syst. VideoTechnol., 7: 477-488.

Choi, E.C., J.S. Choi and M.G. Kang, 2004. Super-resolution approach to overcome physical limitations of imaging sensors. An overview. Int. J. Image. Syst. Technol., 14: 36-46.

Choi, M.J., R.Y. Kim, M.R. Nam and H.O. Kim, 2005. Fusion of multispectral and panchromatic satellite images using the curvelet transform. IEEE Geosci. Remote Sensing Lett., 2: 136-140.

Eismann, M.T. and R.C. Hardie, 2004. Application of the stochastic mixing model to hyperspectral resolution enhancement. IEEE Trans. Geosci. Remote Sensing, 42: 1924-1933.

Farsiu, S., D. Robinson, M. Elad and P. Milanfar, 2004. Advances and challenges in super-resolution. Int. J. Image. Syst. Technol., 14: 47-57.

Freeman, W.T., T.R. Jones and E.C. Pasztor, 2002. Example-based super-resolution. IEEE Comput. Graph. Appl., 22: 56-65.

Gualtieri, J.A. and S. Chettri, 2000. Support vector machines for classification of hyperspectral data. Proceedings of International Geoscience and Remote Sensing Symposium, IGARSS 2000. July 24-28, IEEE., pp: 813-815.

Guo, B.F., S. Gunn, B. Damper and J. Nelson, 2005. Hyperspectral image fusion using spectrally weighted kernels. 8th International Conference on Information Fusion, Philadelphia, PA, 25-28 July, IEEE., pp: 402-408.

Joshi, M.V., L. Bruzzone and S. Chaudhuri, 2006. A model-based approach to multiresolution fusion in remotely sensed images. IEEE Trans. Geosci. Remote Sensing, 44: 2549-2562.

Li, R., B. Zeng and M.L. Liou, 1994. A new three-step search algorithm for block motion estimation. IEEE Trans. Circuits Syst. Video Technol., 4: 438-442.

Lu, Y., M. Inamura and M. Del Carmen-Valdes, 2004. Super-resolution of the undersampled and subpixel shifted image sequence by a neural network. Int. J. Image. Syst. Technol., 14: 8-15.

Manolakis, D., D. Marden and G.A. Shaw, 2003. Hyperspectral image processing for automatic target detection applications. Lincoln Lab. J., 14: 79-116.

Marziliano, P. and M. Vetterli, 2000. Reconstruction of irregularly sampled discrete-time bandlimited signals with unknown sampling locations. IEEE Trans. Signal Proc., 48: 3462-3471.

Merino, M.T. and J. Nunez, 2007. Super-resolution of remotely sensed images with variable-pixel linear reconstruction. IEEE Trans. Geosci. Remote Sensing, 45: 1446-1457.

Munechika, C.K., J.S. Warnick, C. Salvaggio and J.R. Schott, 1993. Resolution enhancement of multispectral image data to improve classification accuracy. Photogram. Eng. Remote Sensing, 59: 67-72.

Ohnishi, N., K. Kumaki, T. Yamamura and T. Tanaka, 1996. Separating real and virtual objects from their overlapping images. Proceedings of the 4th European Conference on Computer Vision Cambridge, UK., April 15-18, LNCS 1065, Springer, Berlin, Heidelberg, pp: 636-646.

Omrane, N. and P. Palmer, 2003. Super-resolution using the walsh functions-a new algorithm for image reconstruction. Proceedings of International Conference on Image Processing, ICIP 2003. Sept. 14-17, IEEE., pp: 299-302.

Pan, M.C., 2002. A novel blind super-resolution technique based on the improved poisson maximum a posteriori algorithm. Int. J. Imag. Syst. Technol., 12: 239-246.

Penn, B.S., 2002. Using simulated annealing to obtain optimal linear end-member mixtures of hyperspectral data. Comput. Geosci., 28: 809-817.

Rajan, D. and S. Chaudhuri, 2001. Generalized interpolation and its application in super-resolution imaging. Image Vision Comput., 19: 957-969.

Rhody, H.E., 2002. Enhancing spatial resolution for exploitation in hyperspectral imagery. Proceedings of the 31st Applied Imagery Pattern Recognition Workshop (AIPR'02). Oct. 16-18, IEEE., pp: 19-28.

Robinson, D. and P. Milanfar, 2006. Statistical performance analysis of super-resolution. IEEE Trans. Image Proc., 15: 1413-1428.

Robinson, G., H.N. Gross and J.R. Schott, 2000. Evaluation of two applications of spectral mixing models to image fusion. Remote Sensing Environ., 71: 272-281.

Schechner, Y.Y., J. Shamir and N. Kiryati, 1999. Polarization-based decorrelation of transparent layers: The inclination angle of an invisible surface. Proceedings of the 7th IEEE International Conference on Computer Vision. Sept. 20-27, IEEE., pp: 814-819.

Stein, D.W.J., S.G. Beaven, L.E. Hoff, E.M. Winter, A.P. Schaum and A.D. Stocker, 2002. Anomaly detection from hyperspectral imagery. IEEE Signal Proc. Magazine, 19: 58-69.

Tanaka, M. and M. Okutomi, 2007. A fast algorithm for reconstruction-based super-resolution and evaluation of its accuracy. Syst. Comput. Jap., 38: 44-52.

Vandewalle, P., L. Sbaiz, J. Vandewalle and M. Vetterli, 2004. How to take advantage of aliasing in bandlimited signals. IEEE Conf. Acoustics, Speech Signal Proc., 3: 948-951.

Vandewalle, P., L. Sbaiz, M. Vetterli and S. Susstrunk, 2005. Super-resolution from highly undersampled images. IEEE International Conference on Image Processing, ICIP 2005. 11-14 Sept., IEEE., pp: 889-892.

Winter, M.E. and E.M. Winter, 2002. Resolution enhancement of hyperspectral data. Aerospace Conference Proceedings. 2002 IEEE, 1523-1529.

Zhang, D., H.F. Lib and M.H. Du, 2005. Fast MAP-based multiframe super-resolution image reconstruction. Image Vision Comput., 23: 671-679.