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Optimum Method Selection for Resolution Enhancement of Hyperspectral Imagery

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Abstract: The study categorizes the most frequent researched areas of resolution enhancement in hyperspectral imagery and emphasizes on their applications, requirements, achievements and limitations of different approaches. An evaluation of the capabilities of different classes of super-resolution algorithms in hyperspectral imagery shows that there is no generic approach to optimally produce high-quality results on general hyperspectral images and the adequacy of an algorithm is a function of multiple factors, namely, access to multisource information, computational complexity, availability of reliable training data for learning-based methods, efficiency of the algorithm and the expected application. It is also shown that spectral mixture analysis based techniques are appropriate for developing high performance and fast super-resolution algorithms in hyperspectral imagery.

Key words: Hyperspectral imagery, learning-based method, resolution enhancement, spectral mixture analysis

INTRODUCTION

Hyperspectral (HS) imagery in remote sensing is a technique for gathering information of the objects on the ground in a wide range of wavelength bands. It provides both spectral and spatial information of the objects. Hyperspectral (HS) images are rich in spectral information but relatively poor in spatial resolution which usually varies from few to tens of meters. The basis for HS imaging stems from the fact that, for any given material, the amount of radiation that is reflected, absorbed, or emitted, i.e., the radiance, depends on the wavelength. Hyperspectral (HS) imaging sensors measure 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, i.e., the spectral signature, can be used to identify specific materials in a scene. 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.

Imaging sensors have finite spatial and spectral resolution, which results in limited resolution recordings of the scene radiance. A direct solution to increase spatial resolution is to reduce the pixel size (the basic unit of image sensor). As the pixel size decreases however, noise that degrades the image quality increases. To avoid the severe effects of 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 High Resolution (HR) image from observed low resolution images. Basic image enhancing methods includes (Gonzalez and Woods, 2003):

- 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

Resolution enhancement algorithms attempt to extract the HR image corrupted by the limitations of the optical imaging system. In inverse problems like this, the source of information, i.e., HR image, is estimated from the observed data, e.g., Low Resolution (LR) image or images (Farsiu *et al*., 2004).

In this study, main areas of research in spatial resolution enhancement of HS images are outlined. A variety of recent studies are categorized based on the theme of the approach. It contains a sufficient background of earlier research in this field in a single article so that it can be used as a basis for a general and quick introduction to various methods. This general

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overview covers technical aspects of different techniques, introduces their proposed applications and finally highlights the advantages and disadvantages of the approaches. By this means, the most important factors in selection of a proper algorithm for Super-Resolution (SR) of HS images with respect to the expected application are suggested. Such a comparison and analysis can be helpful in providing the necessary framework for new research especially by new researchers.

SPATIAL AND SPECTRAL RESOLUTION ENHANCEMENT

Airborne HS imaging sensors produce a three dimensional (3D) data structure (as a result of spatial and spectral sampling), referred to as a data cube (Fig. 1). 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 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.

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, some of the most important properties of spatial and spectral image processing are compared (Mianji *et al*., 2008a).

In measuring the spectral properties of a material through the atmosphere, the absorption and scattering of the atmosphere, the subtle effects of illumination and the spectral response of the sensor must be considered. The recovery of the reflectance spectrum of each pixel from the observed radiance spectrum is facilitated with the use of sophisticated atmospheric compensation codes.

Table 1: Spatial processing vs. 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	Number 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

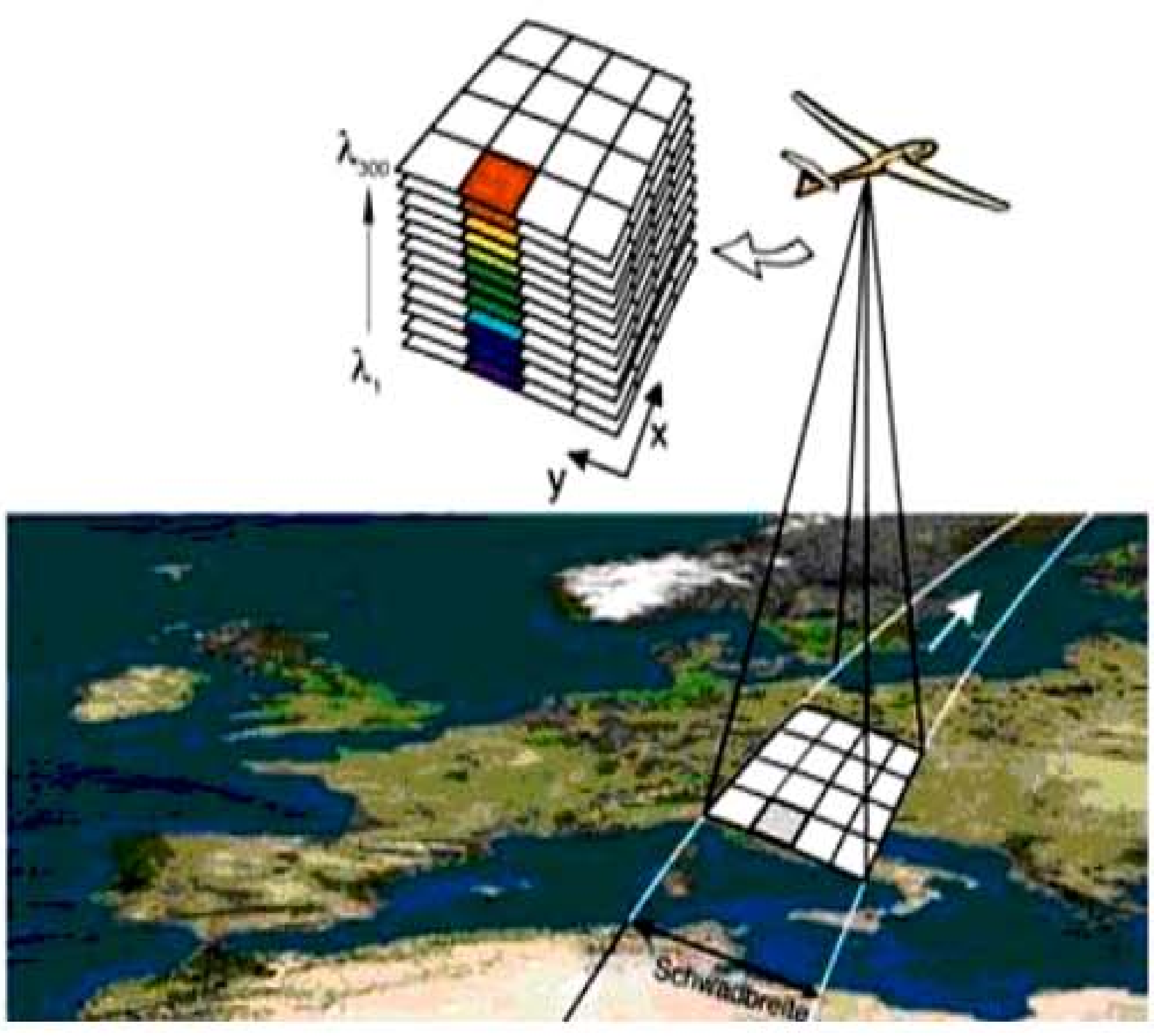

Fig. 1: Data Cube resulted by gathering spatial and spectral information through HS imaging sensor

GENERAL SUPER-RESOLUTION TECHNIQUES

The most common SR approach is capturing multiple LR observations of the same scene by sub-pixel shift in the image sensors motion. This method requires an accurate registration process, which is usually a difficult and challenging task (Joshi *et al*., 2006). In order to overcome this difficulty, in recent years, image processing researchers have started to develop different methods.

Usually, an SR algorithm consists of two steps: image registration and fusing multiple registered LR images into an HR image. Many effective techniques have been developed to do the first step (Li *et al*., 1994; Chalidabhongse and Kuo, 1997). 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. Reconstruction based algorithms to produce an HR image which minimizes the difference between observed LR images and images estimated from the HR image with a camera model have been developed in last decades. These algorithms require iterative calculation and have a large calculation cost due to the fact that reconstruction-based SR is a large-scale problem (Tanaka and Okutomi, 2007). Some research has sought a faster algorithm for solving this problem (Alvarez *et al*., 2004; Zhanga *et al*., 2005).

One of these methods is learning-based method for image SR. In a class of learning-based methods, a database of high-resolution training images is used to create high-frequency details in the zoomed images (Freeman *et al*., 2002; Capel and Zisserman, 2001; Baker and Kanade, 2002). The advantage of learning-based methods is that it provides a very natural way of obtaining the required image characteristics. Requiring a long learning time is the most disadvantage of this method so that limits its applications to an SR problem.

Other sources of problem in imaging are aliasing artifacts and blur. Aliasing artifacts in images are visually very disturbing. Some new methods for reconstruction of an HR image from a set of highly under-sampled and thus aliased images are presented in some articles (Vandewalle *et al*., 2004, 2005; Marziliano and Vetterli, 2000). Tackling the blur through blur reducing techniques has received a great attention too. An example of techniques in overcoming the blur problem is blind SR technique (Lu *et al*., 2004).

All the suggested techniques have limited performance. Some studies concern the performance in SR algorithms and try to find the most effective factors in it. It has been shown that 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 wide open (Farsiu *et al*., 2004).

SPECTRAL MODELS IN HYPERSPECTRAL IMAGERY

Hyperspectral (HS) imaging provides the ability of classification or grouping of similar pixels within an image based on the material content of the pixels. This is especially dominant when there is a considerable number of each class of pixels in a scene and provided that little error in pixels classification is negligible (Manolakis *et al*., 2003). In this case, few misclassifications in hundreds or thousands of pixels are not significant and can not mislead the overall understanding. This is the reason that makes the classification based algorithms in HS imaging an ideal method for environmental investigations. In contrast, target detection applications look for smaller objects usually in the range of man-made objects such as aircrafts and vehicles. There are two factors which makes recognition of the targets even harder: the target may appear in only few or even one pixel of the sensor and the high probability of having a small number of targets in a scene which makes statistical estimation of the target class difficult.

Many algorithms have been developed to detect targets contained within a subspace in HS imaging (Healey and Slater, 1999; Manolakis and Shaw, 2002; Manolakis *et al*., 2000; Novak *et al*., 1999). Target matching approaches are further complicated by the large number of possible objects of interest and uncertainty as to the reflectance/emission spectra of these objects. For example, the surface of an object of interest may consist of several materials and the spectra may be affected by weathering or other unknown factors. One may be interested in a large number of possible objects each with several signatures. Thus, the multiplicity of possible spectra associated with the objects of interest and the complications of atmospheric compensation have lead to the development and application of anomaly detectors that seek to distinguish observations of unusual materials from typical background materials without reference to target signatures or target subspaces. Stein *et al*. (2002) proposed a linear mixture approach to identify target like endmembers based on properties of the histogram of the abundance estimates.

The earlier mentioned limitations justify the efforts towards exploiting the spectral information of HS images. Some of these algorithms aim at improving the recognition ability of the system using sole spectral analysis whereas some other techniques try to enhance the spatial and spectral resolution of the HS images together.

Spectral response of endmembers: Due to its high spectral resolution, HS imaging is more adequate than other techniques in remotely detection of objects such as species of plants on the ground or military vehicles, but it has some limitations on detection of small naturally occurring or man-made objects. Low spatial resolution is also responsible for existence of mixed pixels in HS images, especially on the edges of the objects. Mixed pixels are pixels of the image which contain more than one endmember. Figure 2 shows that how the materials within a ground resolution cell affect the received signal by the corresponding imaging sensor.

There are some sources of nonlinearity in HS imaging such as Bidirectional Reflectance Distribution Function (BRDF) especially in land-cover classification applications (Goodin *et al*., 2004; Sandmeier *et al*., 1999). In landcover applications, depending on the local geometry, BRDF effects lead to variations in the spectral reflectance of a particular category as a function of position in the landscape. Despite these sources of nonlinearity, a frequent assumption in HS remote sensing is that spectral signatures result from linear combinations of endmember spectra (Penn, 2002). These approaches largely ignore the inherent nonlinear characteristics of hyperspectral data (Bachmann *et al*., 2005).

Endmember spectra are endmember components in n-dimensional space. Let L equal the number of endmembers in the spectral library with l ranging from 1 to L. Each spectrum in the library consists of M discrete wavelengths (λ_m) where, m = 1 to M. Let $S^l(\lambda_m)$ represent the spectral response of material l at wavelength λ_m. Each spectrum in the library is described by the following vector:

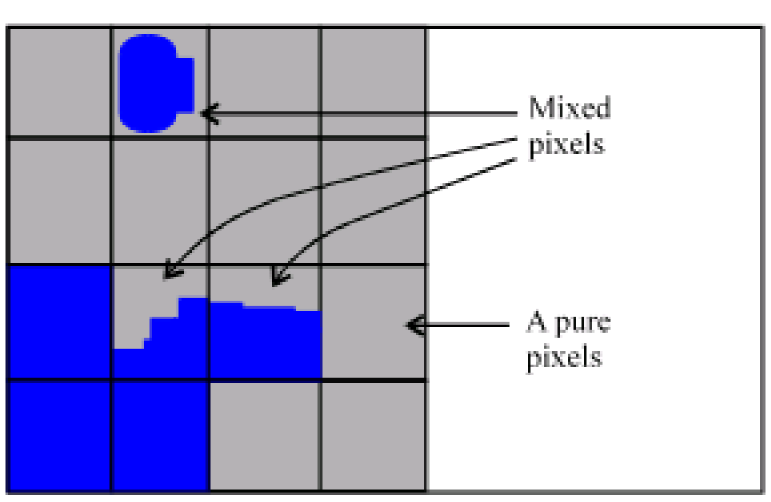

Fig. 2: Pure pixels and mixed pixels

$$s^l = (S^l(\lambda_1), S^l(\lambda_2), \ldots, S^l(\lambda_M)) \quad (1)$$

For an unknown spectra $u = (u_1, u_2, \ldots u_M)$ each vector component is composed of a linear combination of j endmembers from J. u is related to J by the estimation vector $x = (x_1, x_2, \ldots x_L)$ where,

$$0 \le x_l \le 1 \quad (2)$$

And

$$\sum_{l=1}^{L} x_l = 1 \quad (3)$$

For a mixture described by u, the spectral response at λ_m, $S^u(\lambda_m)$, would be as following:

$$S^u(\lambda_m) \sum_l x_l S^l_{\lambda_m} \quad (4)$$

The difference between the calculated spectral response at λ_m and the actual spectral response of u at λ_m is:

$$e_m = (u_m - \sum_l x_l S^l_{\lambda_m}) \quad (5)$$

The goal of spectral unmixing is to minimize e_m. Consequently, the reflectance of a single pixel can be considered as the linear mixture of all the endmembers within a pixel (linear mixture model) (Adams *et al*., 1986; Boardman, 1989; Goetz and Boardman, 1989). Figure 3 shows the spectra for some naturally occurring and man made materials such as concrete and vegetation.

Linear Mixture Model (LMM): Situations of spectral unmixing of HS images in which the endmember

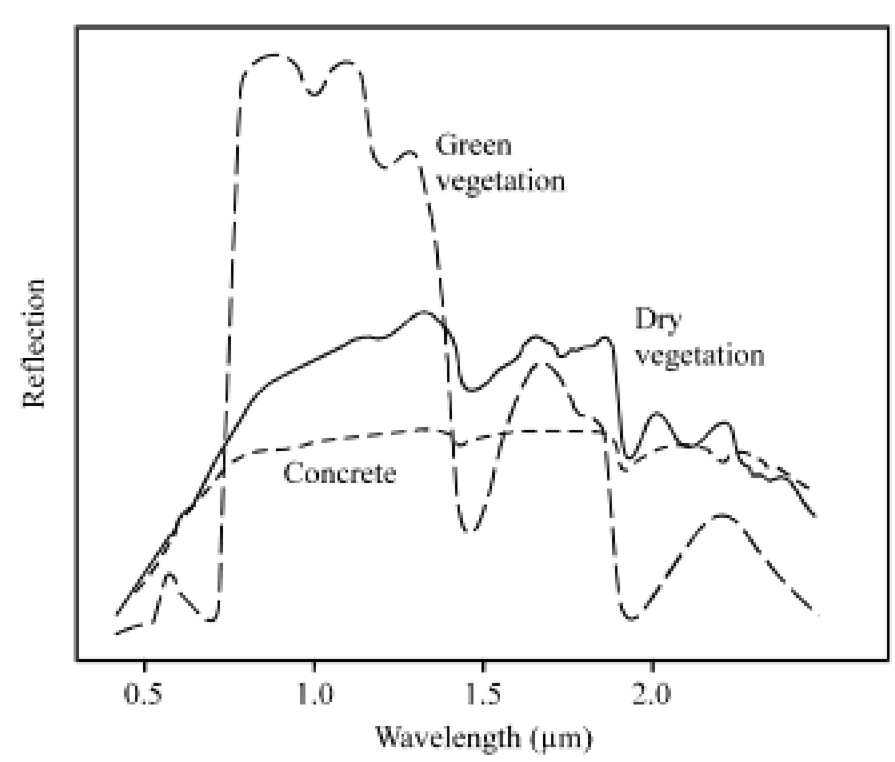

Fig. 3: Sample spectra of some materials

components are distributed in blocklike areas within the Field-of-View (FOV) of the instrument, can be described by LMM (Gu *et al*., 2008). Examples of these situations are when the spectrometer FOV passes over different regions such as fields, lakes, rivers and forests. Under these circumstances, one would expect the resultant reflectance spectrum to be a linear combination of endmembers in the region. Within a given scene, the basic premises of LMM are as follows:

- The surface is dominated by a small number of landcovers with relatively constant spectra
- Most of the spectral variabilities within the scene result from varying proportions of the endmembers.
- The mixing relationship is linear if the endmembers are arranged in spatially distinct patterns

The abundance of each endmember spectrum (weighting factor) is proportional to the fraction of the pixel area covered by the endmember and the spectrum of a mixed pixel is represented as a linear combination of component spectra (endmembers) in the LMM. For M spectral bands, the spectrum of the pixel and the spectra of the endmembers are represented by M-dimensional vectors so that the general equation for LMM is described as a linear regression form

$$z = \sum_{i=1}^{L} a_i s_i + e = Sa + e \tag{6}$$

where, z is an M×1 column pixel vector which describes the spectrum of the mixed pixel, $S = [s_1, s_2, ... s_L]$ is an M×L endmember matrix of material signature, $s_i(i = 1, 2,..., L)$ are the M-dimensional spectra of the endmembers, a is an L×1 column vector and is composed of abundance coefficients $a_i(i = 1, 2,...,L)$, e is an M-dimensional error vector accounting for lack-fit and noise effects and L is the number of the endmembers (Heinz and Chang, 2001; Jia and Qian, 2007).

Generally, Eq. 4 has to follow two constraints of nonnegativity and sum-to-one, based on physical considerations, i.e.,

$$a_i \geq 0 \tag{7}$$

$$\sum_{i=1}^{L} a_i = 1 \tag{8}$$

Equation 6-8 are the expected LMM models.

Endmember extraction: When endmember signatures are known, they can be estimated by quadratic programming such that the constraints are satisfied (Qian, 2004). When the endmember signatures are partially or completely unknown, they can be estimated from the image scene directly using least squares criterion.

The general quadratic program can be written as:

$$\text{Minimize} \quad f(x) = cx + \frac{1}{2} x^T Q x \tag{9}$$

$$\text{Such that} \quad Ax \leq n \;\text{ and }\; x \geq 0 \tag{10}$$

where, c is an n-dimensional row vector describing the coefficients of the linear terms in the objective function and Q is an (n×n) symmetric matrix describing the coefficients of the quadratic terms. The n-dimensional column vector x denotes the decision variables and (m×n) A matrix and an m-dimensional column vector b of right-hand-side coefficients define the constraints. It is assumed that a feasible solution exists and that the constraint region is bounded. When the objective function f(x) is strictly convex for all the feasible points, the problem has a unique local minimum which is also the global minimum.

There are some research that provide detailed introduction about endmember extraction (Chang and Heinz, 2000; Heinz and Chang, 2001; Chang *et al*., 2002; Plaza *et al*., 2002; Chang and Ji, 2006; Plaza *et al*., 2004; Wang and Chang, 2006). Some algorithms have been developed to handle the LMM according both nonnegativity and sum-to-one constraints, these algorithms tend to be computationally intensive as the number of endmembers increases. Among them, Fully Constrained Least Squares (FCLS) algorithm can meet both abundance constraints in an efficient manner; it is optimal in terms of Least Squares Error (LSE) (Heinz and Chang, 2001). The main problem of the FCLS in concrete processing is that, unlike the sum-to-one constraint which can be solved by a closed form solution, it does not have a closed-form mathematical solution for the nonnegativity constraint since it is formed by a set of p linear inequalities rather than equalities; thus, a numerical solution is always required.

In general, a nonnegatively constrained least squares problem can be described by the following optimization problem:

$$\begin{array}{ll} \text{Minimize} & LSE = (Sa - z)^T (Sa - r) \\ \text{Subject to} & a \geq 0 \end{array} \tag{11}$$

where, the LSE is used as the criterion for optimality and $a \geq 0$ represents the nonnegativity constraint so that $a_j \geq 0$ for all $1 \leq j \leq p$.

The solution for these inequalities is possible through a Lagrangian J as follows:

$$J = \frac{1}{2}(Sa - z)^T(Sa - z) + \lambda(a - c) \quad (12)$$

where, $c = (c_1+c_2+....,c_p)^T$ is an unknown p-dimensional positive constraint vector with $c_j>0$ for $1 \le j \le p$ to take care of the nonnegativity constraint.

with a = c and

$$\frac{\partial J}{\partial a}\bigg|_{a} = 0 \Rightarrow S^T S_a - S^T z + \lambda = 0 \quad (13)$$

which results in the following two iterative equations;

$$\hat{a} = (S^T S)^{-1} S^T z - (S^T S)^{-1} \lambda \quad (14)$$

$$\lambda = S^T (z - S_a) \quad (15)$$

In order to satisfy the sum-to-one constraint, a new signature matrix S', is defined by including the constraint in the signature matrix S.

$$S' = \begin{bmatrix} \delta S \\ 1^T \end{bmatrix} \quad (16)$$

with $1 = (1_1, 1_2, ... 1_p)^T$ and a vector z' by:

$$z' = \begin{bmatrix} \delta z \\ 1 \end{bmatrix} \quad (17)$$

where, δ is a constant to control the impact of the abundance sum-to-one constraint and has a typical value of 1×10^{-5} (Broadwater and Chellappa, 2007).

SPATIAL RESOLUTION ENHANCEMENT IN HYPERSPECTRAL IMAGERY

A considerable number of techniques have been recently researched in order to enhance the spatial resolution of HS images (Price, 1987; Nishii *et al*., 1996; Garcia-Haro *et al*., 1996; Atkinson *et al*., 1997; Schowengerdt, 1997; Foody, 1998; Gross and Schott, 1998; Brown *et al*., 1999; Robinson *et al*., 2000; Tatem *et al*., 2001; Winter and Winter, 2002a; Hardie and Eismann, 2004; Eismann and Hardie, 2004, 2005; Mertens *et al*., 2004; Akgun *et al*., 2005; Nguyen *et al*., 2006; Meria and Nunez, 2007). To overcome the intrinsic problem of low LR of HIS, a wide variety of algorithms have been applied. Most of these algorithms are directly based on the joint processing of multisource or multisensor images (Price, 1987; Nishii *et al*., 1996; Robinson *et al*., 2000; Hardie and Eismann, 2004; Eismann and Hardie, 2005). The methods include multiresolution methods, least square estimation, statistical methods, component substitution, joint endmember determination etc. This section categorizes the different proposed techniques for improving the spatial resolution of HS images and highlights the advantages and drawbacks associated with each category.

Joint Processing Method (JPM): Using a secondary source of information is the basis of this approach. These methods can be approximately categorized into two classes. One class uses a broadband panchromatic data as a secondary imaging source to improve the HS image for human interpretation. These approaches impose spatial information of HR image onto the intensity component of the lower resolution image. The deficiency of this algorithm is that, the extent to the spatial enhancement may be limited to the first principal component of the HS image (Eismann and Hardie, 2005). Another class obtains high spatial frequency contents of HR image using high-pass filters and adds the information to the low spatial resolution HS image (Hardie and Eismann, 2004). The result is a higher spatial resolution HS image. The main limitation for all joint processing methods is that they need supplementary spatial information associated with test HS image.

An overview on JPM: Improving the resolution in HS imaging has a high payoff, but applying SR techniques separately to every spectral band is problematic for two main reasons. First, the number of spectral bands can be in the hundreds, which increases the computational load excessively. Second, considering the bands separately does not make use of the information that is present across them. Furthermore, separate band super resolution does not make use of the inherent low dimensionality of the spectral data, which can effectively be used to 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 super resolution to HS image 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.

In another approach, Rhody (2002) proposed a resolution enhancement in target and material identification in remotely sensed data by fusing of spectral information and monochrome images. 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 imagery has been proposed to produce a data set that has higher resolution in both the spatial and spectral domains than that can be obtained with either type of imagery alone.

The SVM classification approach in fusion of HR and HS imagery is also shown to be an effective way to produce a data set that has higher resolution in both the spatial and spectral domains (Gualtieri and Chettri, 2000). Winter and Winter (2002b) suggest a technique, called Joint Endmember Determination, for combining an 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. Another introduced 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).

Also an improved method of image fusion based on the Amélioration de la Résolution Spatiale par Injection de Structures (ARSIS) concept using the curvelet transform is introduced by Choi *et al*. (2005). Their approach is 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 carried out by means of enhancing the edges.

In another research, the development and applications of an SR method, known as SR Variable-Pixel Linear Reconstruction is described by Meria and Nunez (2007). The algorithm works by combining different lower resolution images in order to obtain, as a result, a higher resolution image. It is shown that it can make spatial resolution improvements to satellite images of the Earth's surface allowing recognition of objects with size approaching the limiting spatial resolution of the lower resolution images.

HS imaging is not limited to remote sensing. Its medical and biological applications suffer from instrumental limitations of HS cameras so that make it difficult to perform high-resolution scanning of microscopic samples. Some instrumental scheme and computational method for improving the spatial resolution of HS imaging have been proposed (Munechika *et al*., 1993; Robinson *et al*., 2000). As an example, the increase in scanning resolution of microscopic samples could 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 low resolution 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.

Spectral Mixture Analysis (SMA): The need for a secondary source of information in JPM can be very crucial in many cases and providing it could be very expensive or even impossible sometimes. This is a good reason to develop self sufficient techniques which are able to exploit HS images using their sole content of information. An indirect approach to resolution enhancement is based on Spectral Mixture Analysis (SMA) or sub-pixel classification (Garcia-Haro *et al*., 1996; Atkinson *et al*., 1997; Schowengerdt, 1997; Gross and Schott, 1998; Brown *et al*., 1999; Winter and Winter, 2002; Eismann and Hardie, 2004).

As it is described earlier, the assumption in SMA based algorithms is that the spectral signatures result from linear combinations of endmember spectra. Hence, a Linear Mixing Model (LMM) can be developed for HS imaging. One of the approaches in these techniques is first performing such a modeling. After creating the model, fully constrained least squares algorithm such as linear spectral mixture modeling is utilized to obtain the fractional images which contain abundances of endmembers (Garcia-Haro *et al*., 1996).

Garcia-Haro *et al*. (1996) proposed an alternative approach which appends the high spatial resolution image to the HS data and computes a mixture model based on the joint data set. This technique utilizes the JPM, therefore it is not a pure SMA method.

Observation of spectral signatures from some HS datasets shows that the useful information for classification is not equally distributed across the bands. 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).

Another SMA class of methods estimates landcover components by sub-pixel processing, such as multilayer perceptron neural networks (Atkinson *et al*., 1997), nearest neighbor classifiers (Schowengerdt, 1997), support vector machines (Brown *et al*., 1999) etc. These techniques are able to provide more accurate representation of landcovers than the original HS image.

The advantage of SMA based algorithms is that they can analyze the sub-pixels without other supplementary information. They provide the abundances of endmembers within a pixel which is very useful especially for applications such as object recognition in remote sensing but it only describes mixed pixels by the proportions of the endmembers. In sub-pixel processing, the spatial dependence of land covers in mixed pixels is not utilized in sub-pixel level and the spatial distribution remains unknown. In other word, what the SMA-based method performs is only the preparation stage for the spatial resolution enhancement of HS imaging. They do not substantively enhance the spatial resolution of HS image. That means these methods fail to fully exploit spatial–spectral information.

Super-Resolution Mapping (SRM): Spatial resolution enhancement of HS images without using secondary high spatial resolution sources needs algorithms which are capable of revealing or estimating the spatial dependence of the components within the pixels. This is called Super-Resolution Mapping (SRM) which is a set of techniques to increase the spatial resolution of a landcover map obtained by soft classification methods such as SMA. In addition to the information from the landcover fractional images, supplementary information at the sub-pixel level can be used to produce more detailed and accurate landcover maps (Nguyen *et al*., 2006). Some SRM techniques have been investigated in order to sufficiently utilize the spatial-spectral information of HS images in the last decade. They aim to predict the location of landcover classes within a pixel based on the proportion produced by the SMA. That is to say, SRM can improve the spatial resolution of the resulting landcover maps. In a proposed algorithm by Foody (1998), another higher spatial resolution image is used to improve the output of sub-pixel classification. The main disadvantage of this algorithm is that it is difficult to obtain two coincident images of different spatial resolutions. On the other hand this algorithm needs a secondary source which means it also belongs to JPM class.

Neural networks as extremely versatile tools, has proved their high efficiency in this kind of approaches too. High learning ability of neural networks besides their generalization potential has made them a powerful tool in image processing as many other fields. The spatial distribution of target components within a pixel was expressed as an energy function of a Hopfield Neural Network (HNN) by Tatem *et al*. (2001). The results of this algorithm provide an improved representation of landcovers; however, as it can be expected, this algorithm costs considerable computational time to obtain the results. In a different approach an SRM method based on HNN is proposed by Nguyen *et al*. (2006), which needs a fused image as an additional source of information for SRM. The basis for this method is to model the spatial dependence as an energy function through converting the sub-pixel mapping task into a minimum optimization model. The main disadvantage of the later approach is also the computational cost of the algorithm. Without considering computational time, the HNN-based methods provides an effective approach toward the sub-pixel mapping problem so that it can be used as a benchmark for other algorithms.

Based on the theory of the minimum energy in neural networks, by minimizing the energy function, a best guess map of the spatial distribution of class components in each pixel is reachable. Substituting the energy function, the use of network training can be considered to model spatial dependence.

Spatial-Spectral Joining (SSJ): In a different approach by Gu *et al*. (2008), a complete processing for improving the spatial resolution of HS images by combining the SMA and the SRM together is proposed. The main principle is to sufficiently mine the data advantages of HS imaging by spectral unmixing and SRM and to integrate the spatial-spectral information for resolution enhancement. One advantage of the proposed method is that no supplementary source associated with HS image is needed. The algorithm includes two main steps. First, the abundance of each endmember in a pixel is obtained by linear SMA (LSMA). Second, according to fractional image (abundance) and spatial correlation tendency of landcovers, an SRM model is created and trained by using Back Propagation Neural Network (BPNN) and the spatial-spectral information is integrated for realizing the resolution enhancement. Such processing needs no a priori knowledge of landcovers because the method of endmember extraction can automatically obtain spectra and the number of landcovers, which are used in the LMM construction and FCLS-based solving. It provides both the information of landcovers (i.e., spectral information) and the spatial distribution information of landcovers. The main drawback of this algorithm is its lower but still acceptable resolution compare to HNN based methods and the main advantage is that it offers a much faster response which makes it suitable in real time target recognition and tracking applications.

Mianji *et al*. (2008b) proposed an improved supervised classification technique through applying a sub-pixel mapping method on remotely sensed HS images (Fig. 4, 5). In the proposed technique, classification of the HS image is carried out using spectrally homogenous training classes of pixels. Low spatial resolution frames of different wavelengths of the HS image are fed to a least squares based classification program and the resulted fractional images are processed with an SRM algorithm to enhance the spatial resolution of the classification process. This algorithm improves the spatial dependence of the endmembers within the pixels of the HS image without using any secondary source of image. The disadvantage of this method is also its lower resolution compare to HNN based methods.

C4 = 60% C2 = 40%	C2 = 70% C1 = 30%	C2 = 60% C3 = 40%
C2 = 60% C3 = 40%	C1 = 50% C2 = 30%	C3 = 70% C1 = 30%
C3 = 70% C2 = 30%	C1 = 80% C3 = 20%	C1 = 60% C3 = 40%

Fig. 4: An example of contribution of components in the pixels provided by SMA

			C4	C2	C1			
			C2	C2	C1			
			C1	C1	C1			

Fig. 5: Assigning the components of the middle pixel to its sub-pixels according the abundances in the neighboring pixels

RESULTS AND DISCUSSION

Table 2 shows the advantages and disadvantages of different classes of algorithm in the SR of HS imaging. It is shown that depending on the available sources of information and the expected application, a specific method can be chosen. When a proper HR panchromatic image or multiple HS images are available in an application, maybe the JPM based algorithms are the optimum approach provided that a real time imaging system is not needed. Furthermore, JPM is computationally complex and inadequate for automatic detection purposes.

SMA overcomes the obstacle of being dependent on multiple image sources through exploiting the spectral information of the HS image and is a fast and acceptable method in many object recognition and material analysis applications but it is limited in accuracy and unable in defining the spatial dependence of the components. It is rather a preparation stage for the resolution enhancement of HS images.

SRM combines the abilities of the SMA and some powerful tools like HNN to exploit spatial dependence of the components in HS images. It is an advanced SR approach in utilizing the spatial–spectral information of HS images. SRM suffers from high computational cost but due to its high efficiency has found its application in high resolution HS imaging.

The last introduced method is SSJ which integrates the spatial-spectral information of HS images using tools such as BPNN. It needs no training data associated with

Table 2: A comparison of different SR methods in HS imaging

Algorithm	Advantage	Disadvantage	Main application
JPM	HR panchromatic or other HS images can be used to improve the spatial resolution of an HS image. Some methods can lead to a better classification.	It is a multisource or multisensor technique. The extent to the spatial enhancement may be limited to the first principal component of the HS image.	Almost all HS fields except real time imaging systems.
SMA	It provides more accurate representation of landcovers than the original HS image. It cab be a good preparation stage for many other techniques	It does not substantively enhance the spatial resolution of the HS image.	Object recognition in remote sensing, classification and material analysis.
SRM	For some techniques it is independent of secondary source or image. High performances are achievable.	The computational cost of the algorithm could be high. It requires reliable training samples (ground truth information).	Object recognition in remote sensing and material analysis.
SSJ	It needs no secondary source of image. Training samples may be unassociated with the test HS image. It has low computational cost.	The performance is lower compare to some other techniques.	Real time target recognition and tracking applications.

the test data and no a priori knowledge of landcovers and in terms of consuming time, it is very fast. SSJ has a lower efficiency compare to some SRM techniques but is good in real time target recognition and tracking applications.

CONCLUSIONS

This study shows that there is no unique algorithm to response the requirements of resolution enhancement of HS imaging. It also categorizes the substantive achievements in the last decade and highlights the need for further improvements toward an ideal SR algorithm capable of producing high-quality results on HS imagery. The studied methods include: joint processing technique, spectral mixture analysis, super-resolution mapping and spatial-spectral joining. The paper develops a framework for method selection in SR of HS through precisely considering the applications, requirements, achievements and limitations of each method. The main factors for such an evaluation include, access to multisource information, computational complexity, availability of reliable training data for learning-based methods, efficiency of the algorithm and the purpose of application.

Appreciating the potentials and drawbacks of the studied categories, it concludes that the SMA based approaches are more flexible and applicable for general image enhancement purposes in HS imaging due to their ability in discarding the need for supplementary sources of image. The advantage of being independent of secondary source of data, e.g., HR images, makes the SMA based approaches a proper and powerful basis for further research.

In addition to the lack of a generic SR algorithm capable of producing high-quality results on general image sequences, the question of an optimal resolution factor (r) is still wide open (Farsiu *et al*., 2004). Features such as robustness, computation efficiency and automatic selection of parameters in SR methods are serious obstacles which severely limits their applications in SR of HS imaging. The future plan for this study is to develop a new SMA based algorithm by combining the advantages of SMA and SRM techniques to achieve a higher efficiency and lower computational cost in exploiting HS data.

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