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Subpixel Target Enhancement in Hyperspectral Images

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ABSTRACT

Hyperspectral images due to their higher spectral resolution are increasingly being used for various remote sensing applications including information extraction at subpixel level. Typically whenever an object gets spectrally resolved but not spatially, mixed pixels in the images result. Numerous man made and/or natural disparate targets may thus occur inside such mixed pixels giving rise to subpixel target detection problem. Various spectral unmixing models such as linear mixture modeling (LMM) are in vogue to recover components of a mixed pixel. Spectral unmixing outputs both the endmember spectrum and their corresponding abundance fractions inside the pixel. It, however, does not provide spatial distribution of these abundance fractions within a pixel. This limits the applicability of hyperspectral data for subpixel target detection. In this paper, a new inverse Euclidean distance based super-resolution mapping method has been presented. In this method, the subpixel target detection is performed by adjusting spatial distribution of abundance fraction within a pixel of an hyperspectral image. Results obtained at different resolutions indicate that super-resolution mapping may effectively be utilized in enhancing the target detection at sub-pixel level.

Keywords: Super-resolution mapping, mixed pixel, subpixel target detection, hyperspectral data, linear mixture modeling

1. INTRODUCTION

The hyperspectral imaging has paved the way to uncover targets which used to remain uncovered while analyzing data from multispectral sensors. In most cases, however, the spatial resolution for many satellite based hyperspectral sensors is still too coarse in comparison to their spectral resolution[1]. Thus, a target of interest may get spectrally resolved but may not spatially due to small size. Such a target may partly occupy one pixel or several pixels and may manifest itself in several ways, as can be seen from Fig. 1. For example, a target may lie completely within a pixel or it may cover one pixel fully and also simultaneously exist partially in all the eight pixels in the neighbourhood. In both the cases, the problem is referred to as subpixel target detection. In subpixel target detection, the goal is to recover the target, which due to its smaller size than the spatial resolution is completely embedded in the pixel.

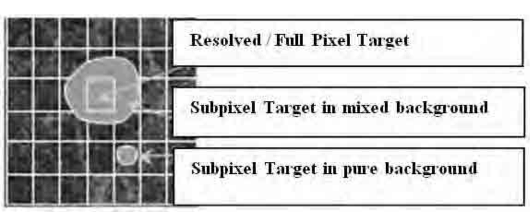

Figure 1. Full and subpixel targets.

Determination of individual components and their abundance fractions inside a pixel is known as mixed pixel classification and is the first step towards subpixel target detection using hyperspectral data. Further, while multipixel target detection can exploit both the spatial and the spectral properties, subpixel target detection can be achieved only by exploiting spectral properties[2]. Since the spectrum of the subpixel target is mixed with the spectrum of the background in a given pixel, it requires unmixing of both the spectrum as well as the proportion of the constituent material (i.e., the abundance fraction). Amongst various unmixing models, linear mixture model (LMM) is the most widely used one for its simplicity[3] despite the fact that it is not guaranteed to produce non-negative abundances and hence there always exists a requirement of a more robust model such as constrained linear mixing model or a nonlinear mixing model for estimating abundance fractions within a pixel. Alternatively, multilayer perceptron neural network and neuro-fuzzy methods[4,5] have also been used to recover the components. These models generally use a priori target information drawn from spectral libraries or from the image scene itself and output both the endmember spectrum and their corresponding abundance fractions inside the pixel. However, abundance fractions thus obtained indicate only their relative proportions and not their spatial distribution within the pixels.

The effective subpixel target detection depends on appropriate spatial distribution of these abundance fractions via super resolution mapping. A number of techniques based on several theories for super resolution mapping have been reported in the literature. These include linear optimization techniques, Markov Random Field models[6], Hopfield neural network[7,8], pixel swapping, etc[9,10] . Most of these techniques

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are still under evolution and testing. These have mostly been applied for land cover mapping with very few implemented for subpixel target detection. In this paper, a new inverse Euclidean distance based super resolution mapping technique for subpixel target detection has been introduced and discussed.

2. EXPERIMENTAL DATA

First set of experiments have been conducted on synthetically generated data with known subpixel abundance fractions, which have been used as reference data to test the proposed technique. Thereafter, the experiments have been repeated on hyperspectral data collected from AVIRIS sensor to detect aircrafts as targets.

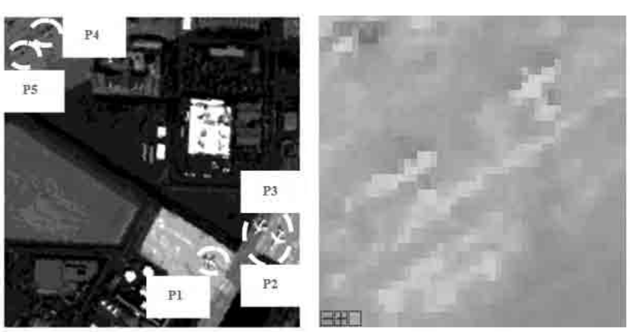
Figure 2. 30x30 pixels image approximating shape of an aircraft. (Fractions ranging from 0.25 to 0.9).

2.1 Synthetic Data

A synthetic dataset approximating the shape of an aircraft and of similar complexity as an actual aircrafts in terms of shape and size has been considered. Further, a number of synthetic images at different scales, namely, 3x3, 5x5, 7x7, 9x9 and 11x11 pixels corresponding to scale factors 3, 5, 7, 9, and 11 respectively have been generated to account for difference in spatial resolutions.

2.2 AVIRIS Data

An archived hyperspectral image (size: 400 x 400 pixels, 224 bands) from AVIRIS sensor acquired over a naval air station in San Diego, California has been used (Fig. 3(a)). The image is available as example data in ENVI image processing software. After removal of water absorption and bad bands, 189 bands of this hyperspectral image already available as reflectance spectra have been considered. The image contains five aircrafts (Fig. 3 (a)) centered at pixel coordinates (row, column), (244, 145), (232,137), (199,158), (89, 11), (70, 22). These have been given reference IDs, P1 to P5. From this data, an image of size 40 x 40 pixels has been extracted containing two aircrafts, P3 and P5 (Fig. 3 (b)). It may be noticed that these two targets fall under shadow and may be treated as difficult targets to detect. For the set of experiments in this study, regions containing both full and partially full pixels have been extracted.



(a) (b)

Figure 3. (a) a 200x200 pixels true colour image of AVIRIS data. (b) 40x40 pixels region of segmented image AVIRIS data with two aircrafts (referred AVIRIS - i).

3. EUCLIDEAN DISTANCE BASED SUPER RESOLUTION

Spectral unmixing is the process by which fractions of various constituents within a pixel (in this case, fraction and the background, also known as abundance fractions) are estimated[11,12]. On the other hand, super resolution may be defined as optimization of abundance fractions within or between the pixels to derive a subpixel map at a spatial resolution finer than that of the coarse spatial resolution input image[6,7,8]. It may be carried out at different scale factors depending upon the spatial resolution required to be achieved. However, developing a model that accurately captures the spatial distribution of abundance fractions within a pixel requires understanding of how natural features get translated into an image.

3.1 Super Resolution Using Abundance Fractions

In nature, all earth surface features exhibit spatial contiguity in their layout and composition. They also appear to hover around a centre of mass. This spatial contiguity also gets retained in the images depicting these features which appear centered around a centre of mass. Thus, all the pixels belonging to that feature (also referred to as class or object or target) are assumed to be attracted towards the pixel in the centre. In other words, the central pixel exerts some attractive influence on all the surrounding pixels of the same class. This attractive influence can be expressed in terms of an attractive function. In a similar way, all subpixels for a given target/class inside a pixel (which can be determined from the knowledge of its abundance fraction) can be assumed to experience an attraction towards the centermost subpixel. Naturally, this attractive influence can be expected to be a function of the distance of any given subpixel from the centermost subpixel and hence can be modeled using an appropriate distance measure. Thus, the attractive influence can be quantified knowing the number of subpixels (expressed in terms of abundance fractions) and the distance of any given subpixel from the centermost subpixel. The genesis of super resolution techniques lies in quantification of this attractive influence.

Modeling the above attractive influence for each pixel to be super resolved requires an appropriate distance function, the number of subpixels for each class and a pixel neighbourhood scheme.. The number of subpixels is calculated based on the scale factor corresponding to the pixel in the coarse spatial resolution image. For example, a scale factor of 5 implies that abundance fractions in a pixel are mapped into five rows and five columns of subpixels. Thus, a total of 25 subpixels are created within each pixel. Further, if a target (or a class) is estimated to have a value of 0.6 as its abundance fraction in a pixel and the scale factor is 5, it implies that 60% of the total subpixels (*i.e*, 25 x 0.6 = 15 subpixels) belong to that target. The next requirement for modeling is the selection of appropriate neighbourhood scheme. Pixel neighbourhood constitutes the group of pixels that exert or experience attraction on/from the central pixel/subpixel. There are several different types of pixel neighbourhood schemes such as 2 x 2 pixels, 4 x 4 pixels and 8 x 8 pixels neighbourhood schemes etc. Each of these pixel neighbourhood schemes also includes the pixel at which the object/class centre is located. Both, the pixel neighbourhood scheme and the object/class centre concepts shall be used in estimation of subpixel distances for modeling attractive influence.

Consider an n x m pixel image, as shown in Fig. 4, to be used for super resolution mapping. It may be noticed that the pixels at the corners are surrounded by other pixels only on three sides while those at the centre are surrounded by eight pixels from different sides. A clique is defined as a subset of an image array whose two distinct elements are mutual neighbours[6]. Thus, for an image array, it is necessary to consider all the possible cliques separately. C1 to C9 are the various possible cliques. Cliques marked as C1 through C8 do not have an 8 x 8 pixel neighbourhood but clique C9 has an 8 x 8 pixel neighbourhood. These cliques are the backbones of super resolution as these decide the number of pixels that directly influence the pixel being super resolved.

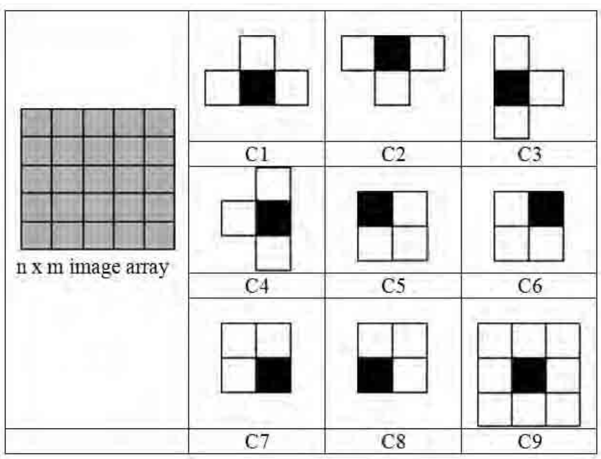


Figure 4. An n x m pixel image array for super resolution and corresponding cliques.

3.2 Modeling the Attractive Influence based on Inverse Euclidean Distance

To understand, modeling of the attractive influence in the case of the proposed inverse Euclidean distance based method, consider an n x m array as shown in Fig. 5 (a) (note that it is the same n x m pixel array as shown in Fig. 4). For super resolution, let a 3 x 3 pixel array be extracted from this pixel array as in Fig. 5(b). Further, consider that the central pixel is the pixel to be super resolved (Fig. 5(c)). This presents a case of clique C9 as shown in Fig. 4. Let all the pixels in this clique be denoted by P1 through P9 (Fig. 5 (c)). Assuming that super resolution is being performed at a scale factor of 5, a 5 x 5 subpixel grid has been created at the central pixel. Thus, there are 25 subpixels which need to be spatially distributed. In other words, there are 25 subpixel locations which are occupied by either of the binary classes but their exact locations are yet to be ascertained. To do this, we need to know the fractions of the binary classes. Let one of the binary classes in the entire 8-pixel neighbourhood be referred as CL-1 and let abundance fractions for this class in each of the pixels, identified as P1 to P9, be a1 to a9 as shown in Fig. 6(b). Once these fractions are known, the number of subpixels for each binary class can be calculated. Consider for example that the fraction for CL-1 in the central pixel is 0.8. Then the number of subpixels of class, CL-1, present in the central pixel is 0.8 x 25= 20 subpixels and rest belong to the other class. Similarly, number of subpixels for each of the binary class inside all the pixels P1 through P9 can be found. The requirement now is to spatially distribute the subpixels of each of the binary classes. In the preceding example, 20 subpixels of Cl-1 and balance 5 subpixels of other class have to be assigned a unique location amongst the total 25 subpixel locations available in the central subpixel. It can be expected that the distribution of these subpixels of say CL-1 (and of the other class) would depend upon two things, namely the abundance fractions of the same class in all the neighbouring pixels of the clique and the distance of each subpixel from the neighbouring pixel. For example, refer to Fig. 6. Assume that there are 20 subpixels of Cl-1 in the central pixel P5. First, the number of subpixels experiencing attraction from each of the neighbouring pixels P1, P2, P3, P4, P6, P7, P8, P9 (*i.e*, excluding P5 which is the pixel being

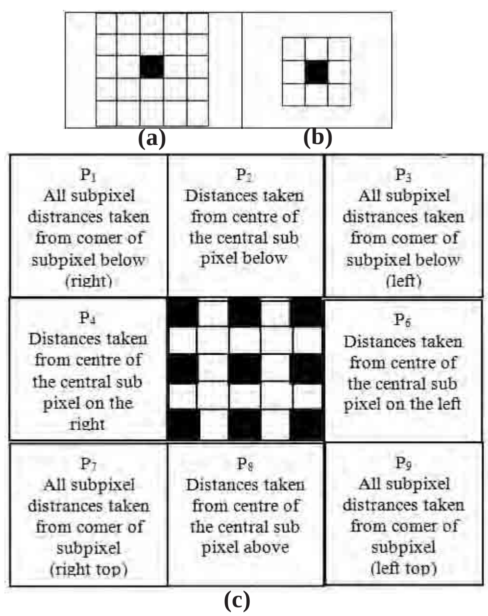


Figure 5. (a) An n x m image array for super resolution, (b) 8 x 8 pixel neighbourhood, and (c) 8 x 8 pixel neighbourhood with central pixel for super resolution mapping.

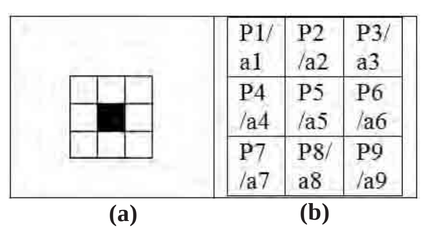


Figure 6. (a) 3 x 3 pixel array, and (b) abundance fractions of Cl-1 in the image.

super resolved) and getting aligned at locations closer to it, will depend upon the abundance fraction of CL-1 in these pixels. In other words, a pixel with higher abundance fraction of CL-1 would attract larger number of subpixels from the pixel being super resolved (*i.e* P5). Second, the attraction experienced by each of the subpixels will be in inverse proportion to its distance from any of the neighbouring pixels. Modelling these two aspects together leads to assigning a unique location to each of the subpixels of both the classes. For the proposed Inverse Euclidean Distance based technique, these aspects have been discussed in the following paragraphs,

3.2.1. Number of Subpixels Getting Attracted Towards Each of the Neighbourhood Pixel

For ease of explanation, assume that the abundance fractions for CL-1 in each of the pixel P1 to P9 (*i.e*, values assigned to a1 to a9 in Fig. 6 (b)) are 0.3, 0.3, 0.3, 0.3, 0.6, 0.2, 0.2, 0.2, 0.2 respectively. Further let the central pixel, P5 be the pixel being super resolved at a scale factor of 5. This means that pixel P5 which is being super resolved has 25 x 0.6=15 subpixels of CL-1 which get attracted towards the class/object centre. During the process of super resolution, it is assumed that the target centre can be located in any of the neighbouring pixels (*i.e*, P1 to P9 except P5 which is under super resolution), and hence each is considered separately in turn as the target centre. Now, the number of subpixels (out of these total 15 subpixels) getting attracted towards each of the neighbourhood pixels P1 to P9 (except P5 which is under super resolution) can be determined. It may, however, be noted that while calculating the number of subpixels getting attracted towards a pixel, the values are always rounded off to the next higher value and the deficiency of subpixels, if any, is accounted towards the pixel having the least abundance fraction.

3.2.2. Estimation of Attractive Influence

In the previous section, the number of subpixels (of pixel P5 under super resolution) getting aligned with each of the neighbourhood pixels (*i.e*, pixels P1 to P9 except pixel P5 which is under super resolution) have been determined. Now, each of these subpixels needs to be assigned a specific location in an array of pixels, the size of the array being determined by the scale factor (as discussed earlier). It is obvious that a subpixel nearer to any given neighbouring pixel will experience greater attractive influence and therefore the relative attractive influence experienced by different subpixels can be used to assign them a specific location. This, however, requires that the attraction being experienced by each of these subpixels from the corresponding neighbourhood pixel is to be determined. Further, it is easy to estimate this attractive influence as a function of the inverse of the distance between the subpixel and any given pixel. Next, for estimating the attractive influence using inverse Euclidean distance, two definite locations are needed namely the start and the finish. The start location is always the class/object centre which is expected to exert attractive influence on the subpixels being super resolved. The finish location is the subpixel of the array on which the attractive influence is being estimated. Since any of the neighbourhood pixel can be the class/object centre, each of the neighbourhood pixel is assumed to be the class/object centre in turn and treated as start location for estimation of the attractive influence. Now, to calculate the Euclidean distance between the two locations, these need to be defined in terms of certain coordinates. To do this, first the pixel to be super resolved is decided and subdivided into a grid of subpixels depending upon the scale factor (in this example, P5 is the pixel being super resolved and the scale factor is 5). All the subpixels can thus be referred to in the form of their row and column coordinates (*i.e* (1,1), (1,2) etc). Next, the locations of all the neighbourhood pixels are also defined in terms of row and column coordinates of the subpixels of the pixel under super resolution. Thus, in Figure 5 (c), the start location in respect of all the corner pixels (P1, P3, P7, P9) are defined as (1,1), (1,5), (5,1), (5,5). Similarly, the start location in respect of all middle subpixels (P2, P4, P6, P8) are defined as (1,3), (3,5), (5,3), (5,1). In the above computations, the inverse Euclidean distance from this class/object centre is defined as,

$$A_{ij} = \left(\frac{1}{d_{ij}}\right) \quad (1)$$

where Euclidean distance is given by,

$$d_{ij} = \sqrt{(i - x_c)^2 + (j - y_c)^2} \quad (2)$$

where d_{ij} is the Euclidean distance, i and j represent row and column coordinates of the neighbourhood pixel assumed to be start location (class/object centre), x_c and y_c are the row and column coordinates of the the subpixel on which the attractive influence is being ascertained

3.2.3. Achieving Super Resolution.

Once the attractive influence experienced by different subpixels from each of the neighbourhood pixels has been estimated, subpixel locations can be ranked in the order of descending attractive influence and these rankings are stored for their subsequent reference during the spatial distribution. At this stage, the number of pixels attracted towards each of the neighbourhood pixels and the ranking of the attractive influence experienced by each of the subpixels are known. It is now assumed that the pixel with the highest abundance fraction for CL-1 shall have the highest attractive influence on the subpixels, therefore the super resolution is commenced with the pixel having the highest abundance fraction. All the subpixels getting attracted to this pixel are considered first and assigned a fixed location as per the stored ranking for this pixel. The process is repeated for the pixel having the next highest abundance fraction for CL–1 and so on until all the pixels of the clique have been processed. During this process, it is ensured that the attractive influence experienced by any single subpixel from any two neighbourhood pixels is never the same. If so, the pixel having higher abundance fraction is assigned higher ranking. The advantages of this ranking procedure are, the attractiveness values for different scale factors can be ranked and stored initially itself and there is no computational requirement at the run time thus making the super-resolution process faster. It considers subpixels of a given class together and hence there is no iterative clustering involved and that it considers the fractions of binary class both in the pixel being super resolved as well as in the neighbouring clique pixels; hence it may be possible to extend the method for various multi-class problems.

4. IMPLEMENTATION OF PROPOSED TECHNIQUE

The implementation of proposed technique can be summarized in the form of an algorithm as,

(a) Obtain the image to be super resolved and estimate the abundance fractions for various classes/targets using spectral unmixing or any other technique.

(b) Decide the scale factor for super resolution. Since there are no heuristics which guide us on the maximum extent to which the input image can be superesolved. This judgement is usually based on trial and error through experiments for a given dataset and the definition of the classes being mapped. In the instant case, scale factor of 3, 5, 7, 9, and 11 were chosen as they were considered sufficient to give adequate enhancement of the target under study.

(c) Calculate attractiveness for each subpixel towards object/class centre.
- Obtain object/class centre points at a given scale factor for all neighbouring pixels in all the cliques.
- Calculate A_{ij} using d_{ij} as given in Eqns (1) and (2).
- Arrange A_{ij} in descending order and store it separately for each of the clique pixels.

(d) Consider the pixel to be super resolved. Obtain abundance fraction for a given class CL-1 in all the clique pixels associated with this pixel and calculate the number of subpixels to be associated to each of the clique pixels.

(e) Commence super resolution,
- Commence super resolution starting with the clique pixel having the highest abundance fraction for any given class.
- Recall the stored rankings for this clique pixel estimated at *step (c)* (iii) and spatially distribute the number of subpixels associated with this pixel.
- Repeat *steps (a) to (e)* till all the clique pixels have been considered. In case of any overlap of subpixel position at any stage, use the next vacant location.

5. RESULTS AND DISCUSSION

5.1 Accuracy of Subpixel Target Detection in Synthetic Data

The classification accuracy and CPU time obtained for the Synthetic image is given in Table 1. It can be seen from the table that classification accuracy achieved using inverse Euclidean distance technique at a scale factor of 11 is as high as 82.22%. The classification accuracy increases marginally from scale factor 3 to scale factor 11 despite the increase in complexity. This suggests that the technique may be more suitable at higher scale factors. On the other hand, the CPU time taken for the proposed technique increases only marginally with the increase in the scale factor. The near constant CPU time for the Euclidean distance technique across all the scale factors demonstrates the effectiveness of the proposed technique in sub-pixel target detection at any given spatial resolution. The main reason for this higher computational efficiency in the proposed technique is the fact that or, it does not involve any iteration as the attractive influence experienced by subpixels for each scale factor is stored *ab initio* itself and are simply recalled at the run time for super resolution process. The targets, recovered using this technique for the synthetic image (shape approximating an aircraft) are shown in Fig. 7. On focusing on the shape of the target (i.e., the aircraft), these figures depict marginal improvement with increase in scale factors. This suggests that there may be improvement in classification accuracy with increase in scale factor without any substantial increase in the CPU time.

Table 1. Classification accuracy and efficiency in case of synthetic dataset

Scale factor	Proposed technique	
	Classification accuracy (%) (s)	CPU Time
3	75.94	09.25
5	81.85	09.25
7	81.65	09.28
9	81.98	09.54
11	82.22	09.59

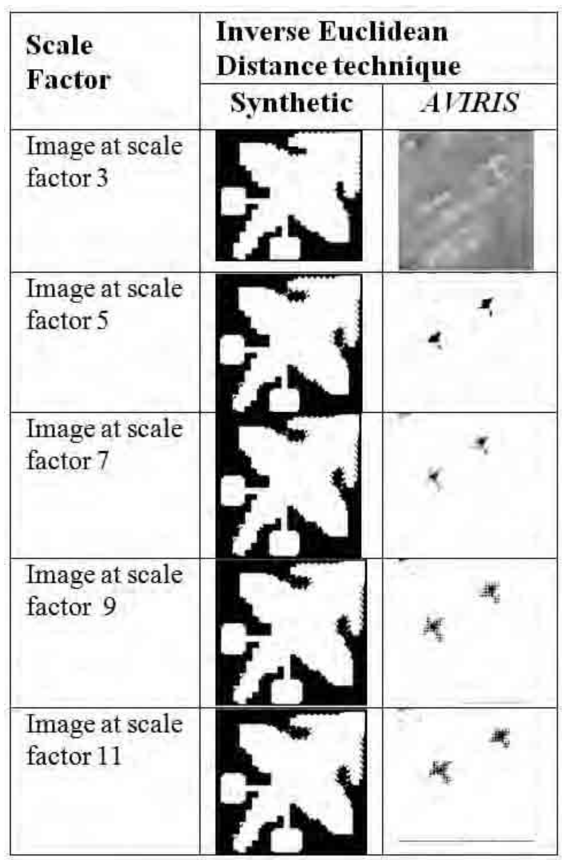


Figure 7. Super resolved images.

5.2 Subpixel Target Detection in AVIRIS

In order to further evaluate the performance of the technique, an AVIRIS has been considered. The dataset consists of two aircrafts as targets. First, the abundance fractions of each pixel in these images have been obtained using the unsupervised spectral unmixing method available as part of ENVI software. It is pertinent to point out here that simple

LMM is not guaranteed to produce non-negative abundances and hence there always exists a requirement of a more robust unmixing model such as constrained linear mixing model or a nonlinear mixing model may for obtaining an accurate estimate of abundance fractions within a mixed pixel. However, for reasons of computational simplicity and to maintain the focus of the study, simple LMM has been used here. Thereafter, the proposed technique has been applied to perform super resolution. However, due to non-availability of reference data, the super resolved images have been evaluated visually and not quantitatively. The super resolved significant increase in CPU time. Images of targets detected across different scale factors are shown in Fig. 7. As is evident from this figure, the proposed inverse Euclidean distance technique produces satisfactory results across all scale factors. The reason for success of this method lies in the fact that it does not involve any iterative convergence and is based on the stored rankings of attractiveness values of the super resolved subpixels. The major advantage of the proposed technique has been the near constant CPU processing time despite increase in scale factor or in complexity (*i.e* synthetic *vs* AVIRIS data).

6. CONCLUSIONS

Spectral unmixing methods such as linear mixture modeling (LMM) are used to recover abundance fractions of the components occurring inside a mixed pixel, There are two main limitations of LMM. The simple LMM is not guaranteed to produce non-negative abundances and hence there always exists a requirement of a more robust unmixing model such as constrained linear mixing model or a nonlinear mixing model may for obtaining an accurate estimate of abundance fractions within a mixed pixel. The second limitation of LMM is its incapability to provide spatial distribution of the abundance fractions within a pixel. These limitations, in particular its incapability to provide spatial distribution severely restricts the applicability of hyperspectral data for subpixel target detection. In this paper, a new inverse Euclidean distance based super-resolution technique has been proposed. The technique achieves subpixel target detection in hyperspectral images by adjusting spatial distribution of abundance fraction within a pixel. The experiments have been conducted using synthetic as well as AVIRIS dataset. The performance of the proposed technique measured in terms of classification accuracy and CPU time for both the datasets have been found be satisfactory and encouraging. The major advantage of the proposed technique has been the near constant CPU processing time despite increase in scale factor or in complexity (i.e synthetic *vs* AVIRIS data).Though the technique produces good results, one of the limitation of the proposed technique lies in the use of a linear Euclidean distance as a measure of attractiveness. Future studies may consider the use of a non-linear measure for ranking subpixels for spatial distribution, particularly in case of multi-class problems.

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(Brief Biodata available on page no. 63)

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