Hyperspectral Image Dimension Reduction and Target Detection Based on Weighted Mean Filter and Manifold Learning

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Abstract. Hyperspectral images have many bands, resulting in a high data volume, which complicates subsequent data processing. Using manifold learning methods to reduce the dimension of data is conducive for subsequent use. However, traditional manifold learning methods are easily disturbed by spectral uncertainty, and are primarily used for hyperspectral image classification. This paper proposes an improved manifold reconstruction preserving embedding algorithm based on weighted mean filter (WMF-IMRPE), that is not easily affected by spectral uncertainty and has excellent target detection performance. The original hyperspectral image is processed by the weighted mean filter to eliminate the influence of noise and reduce spectral differences between the homogeneous ground objects. The spectral angular distance then replaces the Euclidean distance in the original MRPE algorithm to select neighbourhood pixels, reducing spectral uncertainty interference. The experimental results show that the low dimensional features extracted by the WMF-IMRPE algorithm have better distinguishability, and the algorithm further improves the target detection accuracy. The WMF-IMRPE algorithm’s hyperspectral image target detection performance is superior to other similar algorithms.

1. Introduction
Hyperspectral images play an important role in both military and civilian fields due to their unique advantages such as the combination of image and spectrum, wide spectral band range, and high spectral resolution[1-3]. However, hyperspectral images also have the characteristics of large data volume, high data dimensions, and redundant information. The large data volume complicates the storage and transmission of hyperspectral image data. The high dimension of the data causes the hyperspectral image processing process to take time, and the “Hughes” phenomenon exists in the process[4-7]. Therefore, eliminating redundant information and reducing the dimension effectively are vital for the application of hyperspectral image data.

In recent years, scholars have proposed a series of dimension reduction methods for hyperspectral data. Principal component analysis (PCA)[8] and linear discriminant analysis (LDA) [9] are two classic feature extraction algorithms. Both PCA and LDA are linear methods, while hyperspectral data are nonlinear data. Therefore, the nonlinear methods are proposed, and manifold learning is a typical nonlinear technique. Typical manifold learning algorithms include local linear embedding (LLE)[10] and Laplacian eigenmaps (LE)[11]. However, none of these algorithms can generalise new samples. To solve this problem, scholars have created linear approximation to LLE and LE algorithms, and
proposed linear methods such as neighbourhood preserving embedding (NPE)[12] and locality preserving projection (LPP)[13], which have good dimension reduction effects.

The above feature extraction algorithms only use the spectral information of hyperspectral image data to reduce the dimension. However, hyperspectral images also contain a wealth of spatial information, which is not used. If one pixel belongs to a certain class, the closer another pixel is to it in spatial position, the higher the possibility that they belong to the same class. Besides, it can be seen from the distribution of ground objects in the hyperspectral image that the homogeneous ground objects are usually distributed in a concentrated manner or blocks in the image. Based on this characteristic, scholars have studied the comprehensive utilisation of hyperspectral images’ spatial and spectral information to improve the performance of feature extraction algorithms. For example, Wei et al. proposed spatial coherence-neighbourhood preserving embedding (SC-NPE)[14]. Huang et al. proposed a feature extraction algorithm based on the weighted mean filter (WMF) and manifold reconstruction preserving embedding (MRPE)[15]. This algorithm comprehensively utilises hyperspectral images’ spatial and spectral information by spatial filtering and adjusting the weight of spatial neighbourhood pixels.

In the MRPE algorithm, the Euclidean distance is used as the similarity measure function to select neighbourhood pixels. However, spectral uncertainty may affect the selection of neighbourhood pixels and then seriously impact dimension reduction. To solve this problem, this paper proposes an improved manifold reconstruction preserving embedding algorithm based on the weighted mean filter (WMF-IMRPE). The spectral angular distance can overcome the disturbance error caused by spectral uncertainty to a certain extent and improve the construction accuracy of the neighbourhood graph. Therefore, the WMF-IMRPE algorithm uses spectral angular distance instead of Euclidean distance as the similarity measurement function. The existing feature extraction algorithms, including the original MRPE algorithm, are usually used for classification, and there are few related studies on feature extraction algorithms for target detection. In this paper, the WMF-IMRPE algorithm is used for target detection to improve target detection while reducing the dimension of data. Experimental results based on different hyperspectral data sets and various target detection operators show that WMF-IMRPE is superior to other similar algorithms.

2. Methods

2.1. Weighted mean filter

In the hyperspectral imaging process, due to the influence of noise and other factors, homogeneous ground objects’ spectral curves often show differences, that is, the "same body with different spectrum." When the image dimension is high, these differences will negatively impact the similarity measurement between pixels, complicating their subsequent use, such as target detection or classification. Noise in training samples also has a considerable influence on the NPE algorithm. As a variant of NPE, noise also has a significant impact on the MRPE algorithm. However, due to the limitations of observation conditions and sensors, hyperspectral images inevitably contain a high amount of noise, limiting the accuracy of subsequent processing and applications, such as target detection, classification, and unmixing. Therefore, it is necessary to manage noise in the hyperspectral image.

Gaussian noise is commonly present in digital images such as hyperspectral images, and WMF has a better effect on Gaussian noise. Hyperspectral images provide rich spatial and spectral information, but most of the feature extraction algorithms only use hyperspectral images’ spectral information. The WMF is a type of spatial filtering. Before feature extraction of hyperspectral image data, spatial filtering is carried out on hyperspectral images to comprehensively utilise their spatial and spectral information. The WMF also has the advantages of rapid operation and simple principle.

The WMF principle is described as follows:
$X = \{x_1, x_2, \ldots, x_n\}$ represents a hyperspectral image, where $x_i \in \mathbb{R}^D, (i = 1, 2, \ldots, n)$ is any image pixel sample point, $D$ is the hyperspectral image’s dimension, that is, the total number of bands, and $n$ is the total number of samples.

A $w \times w$ square window $\Omega(x_i)$ is constructed that is centred on pixel $x_i(p, q)$, where $p$ and $q$ are row coordinates and column coordinates of pixel $x_i$ in hyperspectral images, respectively. $\Omega(x_i)$ is defined as a neighbourhood space as follows:

$$\Omega(x_i) = \{x_s(p, q_s)\},$$

where $w$ is a positive odd number, $r = (w-1)/2$, and $x_s(p, q_s)$ is the $s$ pixel in the neighbourhood space $\Omega(x_i), 1 \leq s \leq w^2$. Because the neighbourhood space of pixels on the edge of the hyperspectral image makes it impossible to construct a complete window, the proposed algorithm uses the pixel $x$ to the missing part in the process.

The new pixel $\bar{x}_i$ is obtained after WMF as follows:

$$\bar{x}_i = \frac{1}{\sum_{s=1}^{w^2} v_s} \sum_{s=1}^{w^2} v_s x_s, x_s \in \Omega(x_i)$$

where $v_s$ is the weight from pixel $x_s$ to central pixel $x_i$:

$$v_s = \exp\left(-\frac{1}{t}\|x_i - x_s\|^2\right),$$

$t \geq 0$.

Equation (2) and Equation (3) demonstrate that the WMF not only uses the neighbourhood information on spatial location but also takes into account the spectral variations between different pixels. By adjusting the window size $w$ and weight parameter $t$, the filtering degree is controlled, the influence of noise is eliminated, and the spectral similarity between homogeneous pixels is improved.

2.2. Improved Manifold Reconstruction Preserving Embedding based on Weighted Mean Filter

The core of the manifold learning method is the selection of neighbourhood pixels and the construction of adjacency weight matrix. In hyperspectral images, pixels in adjacent positions are composed of homogeneous ground objects in a large probability; the closer the spatial distance, the higher the probability. This is the spatial consistency property of the distribution of the ground objects in hyperspectral images. Based on this characteristic, the manifold reconstruction preserving embedding (MRPE) algorithm can utilise the spatial neighbourhood information of hyperspectral images. For manifold learning methods, including MRPE, the Euclidean distance is used as the similarity measure function between samples to select neighbourhood pixels in the first step. However, due to the widespread presence of spectral uncertainty, the spectral curve’s amplitude of the homogeneous ground objects often changes considerably. When selecting neighbourhood pixels, using the Euclidean distance as the similarity measurement function will probably produce large errors that will cause the pixels to be homogeneous ground objects in low-dimensional data farther from each other. The target detection or classification performance of low-dimensional data may be reduced. In contrast, the spectral angular distance can overcome the disturbance error caused by the spectral uncertainty to a certain extent. Therefore, the WMF-IMRPE algorithm proposed in this paper uses the spectral angular distance instead of the Euclidean distance as the similarity measurement function.
between pixels to reduce the error caused by spectral uncertainty to improve the target detection performance of low-dimensional data.

The steps of WMF-IMRPE algorithm are as follows:

Step 1: The original hyperspectral image is processed using the weighted mean filter with the Equation (2).

Step 2: Neighbourhood selection: The WMF-IMRPE algorithm calculates the spectral angular distance between each sample point \( x_i \) and all of the other sample points, and selects \( k \) sample points with the closest spectral angular distance. The spectral angular distance between pixel \( x_i \) and pixel \( x_j \) is shown in Equation (4). Once the spectral angular distance between different pixels is calculated, the spectral nearest neighbourhood \( k(x_i) \) is selected.

\[
d(x_i, x_j) = \arccos \left( \frac{\sum_{b=1}^{D} x_{ib} x_{jb}}{\left( \sum_{b=1}^{D} x_{ib}^2 \right)^{1/2} \left( \sum_{b=1}^{D} x_{jb}^2 \right)^{1/2}} \right)
\]

where \( x_{ib} \) and \( x_{jb} \) are the values of \( x_i \) and \( x_j \) in band \( b \), respectively.

Step 3: calculating and adjusting the neighbourhood weight matrix: The pixel \( x_i \) is linearly reconstructed by its spectral neighbourhood \( k(x_i) \), and the neighbourhood weight matrix is obtained by minimizing the reconstruction error. The objective function is defined as:

\[
\min w_i = \sum_{j=1}^{N} \left( d_{ij} - \sum_{i=1}^{N} w_{ij} x_j \right)^2 \sum_{j=1}^{N} w_{ij} = 1.
\]

In Equation (5), \( w_i \) is the neighbourhood weight vector corresponding to the sample \( x_i \), and \( x_j \) is the \( j \) nearest neighbor point of the sample \( x_i \). \( w_{ij} \) is the weight between \( x_i \) and \( x_j \). The Lagrange multiplier method is used to solve \( w_i \). After solving the neighbourhood weight vector \( w_i \) of each sample point, it is expanded into an \( n \times n \) neighbourhood weight matrix \( W \) according to the corresponding positions of the neighbor points. To improve algorithm’s performance, the spatial neighbor information is incorporated into the neighbourhood weight matrix. When the pixel \( x_u \) is the spectral nearest neighbor of \( x_i \) and is located in the neighbourhood space of \( x_i \), the weight between the pixels is adjusted:

\[
S_\beta = \begin{cases} \beta w_{ij}, & x_j \in k(x_i) \text{ and } x_j \in \Omega(x_i), \\ w_{ij}, & x_j \in k(x_i) \text{ and } x_j \notin \Omega(x_i). \end{cases}
\]

In Equation (6), the weighted parameter \( \beta \geq 1 \).

Step 4: Calculating low-dimensional embedding: The WMF-IMRPE algorithm keeps the adjusted neighbourhood weight matrix \( S \) unchanged while achieving dimension reduction. The cost function is defined according to Equation (7):

\[
\text{min}(Y) = \sum_{i=1}^{N} \left\| y_i \right\|^2 - \sum_{i=1}^{N} w_{ij} y_i \sum_{i=1}^{N} \left\| Y - YW \right\|^2 \\
= \text{tr}\left( (Y - W)(1 - W)^T Y^T \right) = \text{tr}(YM^T)
\]

In Equation (7), \( \text{tr} \) is the trace of the matrix \( M = (1 - W)(1 - W)^T \). By substituting \( Y = A^T X \) into Equation (7) and under the restricted condition of \( YY^T = n1 \), the projection matrix can be calculated using the Lagrange multiplier method:
By solving the eigenvectors corresponding to the $d$ smallest eigenvalues of the matrix $(XX^T)^T XMX^T$, we can solve the projection matrix $A$, and the projection matrix $A$ is the matrix composed of these $d$ eigenvectors. The low dimensional sample set $Y$ can be obtained by substituting $A$ into $T=YA^TX$.

3. Experiments Analysis and Results

In this section, we use two real datasets to evaluate the proposed algorithm’s efficacy. For a comprehensive comparison, we use various feature extraction algorithms to evaluate the proposed algorithm’s performance. It includes linear PCA and nonlinear NPE, LPP, and LLTSA methods. To further evaluate the proposed algorithm’s performance, we respectively use ACE, CEM, and GLRT target detection operators on two datasets to conduct experiments. We use the receiver operating characteristic (ROC) curve, which is widely used for the performance evaluation of target detection related applications, to evaluate the proposed algorithm’s performance. For the parameter analysis part of WMF-IMRPE and its comparison algorithm, see https://github.com/renwoxing2019/Parameter-Analysis.

3.1. Dataset Description

We use two real hyperspectral datasets intercepted from the AVIRIS San Diego airport dataset to evaluate the proposed method’s efficacy. This image capturing an airport in San Diego, CA, USA, was recorded by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor. The size of the image is $400 \times 400$ pixels, and the spatial resolution is 3.5m per pixel. This image has 224 bands ranging from 370 to 2510 nm. After removing the water absorption region, low signal-to-noise ratio (SNR) and bad bands (1-6, 33-35, 97, 107-113, 153-166, and 221-224), 189 bands were left.

(1) AVIRIS San Diego airport dataset 1 contains complex background object categories. Figure 1 (a) and (b) show bands 1 and 189 of the intercepted image, respectively. There are 38 targets of interest in the image, a total of 432 pixels, and the distribution is shown in Figure 1 (c).

(2) AVIRIS San Diego airport dataset 2 has fewer targets in this dataset, and the terrain is less undulating. Figure 2 (a) and (b) show bands 1 and 189 of this dataset. There are three targets of interest in the image, with a total of 112 pixels, and the distribution is shown in Figure 2 (c).

![Figure 1](image1.png) ![Figure 2](image2.png)

Figure 1. AVIRIS San Diego airport dataset 1 for the experiment. (a) Band 1 image; (b) Band 189 image; (c) The targets’ true locations.
3.2. Detection Results and Analysis

In this subsection, we use ROC curve and target-background separation graph to quantitatively evaluate the performance of the proposed algorithm. The target-background separation diagram can directly show the separation of target and background pixels.

Figure 3 shows the ROC curves of all of the algorithms. For AVIRIS San Diego airport dataset 1, the ROC curves of NPE, LLTSA, and PCA are far from the upper left corner regardless of the type of target detection operator being used, which indicates that they cannot detect all of the target pixels in a reasonable FAR range. The LPP algorithm’s performance is slightly better, but its ROC curve is always under the proposed algorithm’s ROC curve. For AVIRIS San Diego Airport dataset 2, NPE and LPP have similar performance, and LLTSA and PCA have similar performance. The ROC curve of the proposed algorithm is always higher than that of the other four comparison algorithms. Therefore, the proposed algorithm has the optimal target detection performance on all of the datasets.

Figure 2. AVIRIS San Diego airport dataset 2 for the experiment. (a) Band 1 image; (b) Band 189 image; (c) The targets’ true locations.

Figure 3. ROC curves of the different algorithms: (a) ACE detection results on AVIRIS San Diego Airport dataset 1; (b) CEM detection results on AVIRIS San Diego Airport dataset 1; (c) GLRT detection results on AVIRIS San Diego Airport dataset 1; (d) ACE detection results on AVIRIS San Diego Airport dataset 2; (e) CEM detection results on AVIRIS San Diego Airport dataset 2; (f) GLRT detection results on AVIRIS San Diego Airport dataset 2.
Figure 4. Target-background separation maps of the different algorithms: (a) ACE detection results on AVIRIS San Diego Airport dataset 1; (b) CEM detection results on AVIRIS San Diego Airport dataset 1; (c) GLRT detection results on AVIRIS San Diego Airport dataset 1; (d) ACE detection results on AVIRIS San Diego Airport dataset 2; (e) CEM detection results on AVIRIS San Diego Airport dataset 2; (f) GLRT detection results on AVIRIS San Diego Airport dataset 2.

To better compare the separability of the target and background, the target-background separation diagrams of different algorithms are shown in Figure 4, in which the lines at the top and bottom of each column represent extreme values. The red boxes represent the distribution of target pixels, and the green boxes represent the distribution of background pixels. As shown in Figure 4 (a) - (c), for AVIRIS San Diego airport dataset 1, regardless of the type of target detection operator being used, only the proposed algorithm achieves the complete separation of target and background pixels. As shown in Figure 4 (d) - (f), for AVIRIS San Diego airport dataset 2, the gap between the target and the background boxes obtained by the proposed algorithm is the largest. These results demonstrate that the proposed algorithm has an excellent performance in distinguishing target from background pixels.

The two-dimensional detection maps are obtained when the proposed algorithm and its comparison algorithms separately combing with three target detection operators are shown in Figure 5. The higher the brightness, the higher the probability of detection of the target in interest. The proposed algorithm has the best overall performance, which highlights the target pixels and suppresses the background.
4. Conclusion

To effectively reduce the dimension, eliminate the redundant information in hyperspectral image data, and improve its target detection performance, an improved manifold reconstruction preserving embedding algorithm based on weighted mean filter is proposed. Before feature extraction of the hyperspectral image, the WMF-IMRPE algorithm first performs weighted mean filtering on the original hyperspectral image to eliminate the influence of noise and reduce the spectral difference between homogeneous ground objects. To reduce the impact of spectral uncertainty on dimension reduction, the WMF-IMRPE algorithm uses spectral angular distance instead of Euclidean distance as a similarity measure function. To verify the algorithm’s efficacy, we combined three different target detection operators to conduct experiments on two hyperspectral images. We also compared four commonly used dimension reduction algorithms using the same target detection operators and data. The experimental results showed that the WMF-IMRPE algorithm proposed in this paper was more effective than the typical dimension reduction algorithm.
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