Unsupervised Hyperspectral Band Selection Using Clustering and Single-layer Neural Network
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Résumé
Les images hyperspectrales fournissent des détails de la scène observée en exploitant les bandes spectrales continues. Cependant, le traitement de ces images est long à cause de leurs grandes dimensions. Donc, la sélection des bandes est une pratique commune qui est adoptée avant qu’un traitement soit fait. Ainsi, dans ce travail une nouvelle approche non-supervisée pour la sélection des bandes, basée sur le clustering et les réseaux de neurones, est proposée. Une comparaison avec six autres approches de sélection de bandes montre la validité de l’algorithme proposé.

Mots clés : Sélection de bandes, Non-supervisé, Clustering.

Abstract
Hyperspectral images provide rich spectral details of the observed scene by exploiting contiguous bands. But, the processing of such images becomes heavy, due to the high dimensionality. Thus, band selection is a practice that has been adopted before any further processing takes place. Therefore, in this paper, a new unsupervised method for band selection based on clustering and neural network is proposed. A comparison with six other band selection frameworks shows the strength of the proposed method.

Keywords : Band selection, Unsupervised, Clustering

1. Introduction
Hyperspectral images (HSI) are composed of many continuous bands of the electromagnetic spectrum (Chang, 2003). Thus, a broad range of this spectrum can be covered, which provides lots of information about the scene under analysis. Consequently, those images are of great interest to Remote Sensing and Pattern Recognition, because they make easier some tasks such as image classification and target detection.

In a Pattern Recognition System (Duda et al., 2001), however, a large amount of bands can bring problems in terms of data storage and transmission. Moreover, the high dimensionality of HSI can cause the curse of dimensionality for the classifiers (Hughes, 1968). Thus, in order to solve those problems, dimensionality reduction is normally adopted.

To reduce the dataset dimensionality, feature extraction (FE) is a commonly used method (Silva et al., 2013). In sum, FE makes new features by combining the original ones. The resulting features belong to a feature space with lower dimension, keeping much of the original data variance. One largely used FE technique is Principal Components Analysis (PCA) (Sharma, 1996). PCA, as well as other FE techniques, changes the original dataset information, therefore it should not be used when the physical meaning of individual bands is to be kept (Khalid et al., 2014).

Like FE methods, band selection (BS) algorithms also decrease the dimension of the feature space, by selecting bands considered to be relevant, under a certain criterion. The positive aspect, in this case, lies in the fact that the original information is kept (Li and Liu, 2017).

BS algorithms are classified in two categories : supervised and unsupervised. Supervised band selection approaches normally outperform unsupervised ones (Yang et al., 2011). However, the former needs labeled training samples, which are expensive to be collected. Therefore, unsupervised methods are a wise alternative for band selection.

Unsupervised BS methods perform their job without knowing the class information of the data samples, which means that neither class separability measures nor classification accuracies can be used to assess the quality of the selected bands. Instead, the band selection is made by taking into account the data structure (Chandra and Sharma, 2015).

As k-Means algorithm is an unsupervised technique that clusters data samples according to the dataset structure in the feature space (Theodoridis and Koutroumbas, 2008), it will be used in this paper in the proposed band selection framework.
Thus, we propose an easily implementable unsupervised band selection framework. It uses two tools: 1) \(k\)-Means clustering — following a bisecting \(k\)-Means fashion (Banerjee et al., 2015) ; and 2) single-layer neural networks (SLNN) (Haykin, 2009). Initially, the whole data set is clustered by \(k\)-Means into two groups. After that, a SLNN is used to find a hyperplane that separates those two clusters, and the bands linked to the biggest and smallest coefficients of the hyperplane equation are selected. This procedure just described represents one iteration of the method, and two bands are selected at each iteration. If more bands are needed, another iteration is done taking as input data either of the clusters just generated, instead of the whole data set.

The contributions of this paper are the following:

- It is a novel band selection framework based on bisecting \(k\)-Means clustering and single-layer neural network.;
- We compare the proposed method with other six unsupervised band selection algorithms.

This paper is organized as follows: In Section 2, a literature review is presented. Section 3 describes the proposed method. In Section 4, one can find the data-sets, classifiers, the competitors and the results. Finally, Section 5 provides a conclusion to this paper.

2. Literature Review

In the literature, we find lots of hyperspectral band selection papers following many different perspectives and methodologies, such as data manifold, data information analysis, graph theory, evolutionary computation and clustering.

2.1. Data manifold

Due to the high HSI dimensionality, the different classes present in the image may lie in manifolds embedded in subspaces of the original feature space. Furthermore, it is also possible to explore the sparsity of the data set in order to find a more meaningful data representation. For example, in (Wang et al., 2016), the authors propose a new method in which they look for salient bands. The number \(\sigma\) of selected bands is user-defined. Then, the band selection algorithm has two steps. Firstly, \(\beta\) bands are selected by means clone selection algorithm, which seeks to minimize the Euclidean distance amongst elements of the same class, whereas maximizing the distance of elements from different classes. After that, if \(\beta < \sigma\), those \(\beta\) bands already chosen will serve as seeds to a Manifold Ranking (MR) algorithm. MR sorts the remaining bands, and the most dissimilar band is added to the \(\beta\) group. This step is repeated until \(\beta = \sigma\). In (Wang et al., 2017), the authors propose a BS framework based on sparsity. Initially, the most representative bands are obtained according to the correlation matrix, whereas the block-diagonal structure is measured to segment bands into subspaces. Then, a method for band selection based on trace LASSO and spectral clustering is used. In (Sun et al., 2015), the authors propose a method that initially represents data instances as sparse coefficient vectors by solving a L2-norm optimization using the least squares regression (LSR) algorithm. Then, a correct segmentation of band vectors is made using the resulting LSR matrix with sparse and block-diagonal structure. After that, a similarity matrix is constructed by angular similarity measurement, and then the size of the band subset is calculated by the distribution compactness plot algorithm. In (Gan et al., 2017), the authors state that all HSI bands can be represented by a band subset. Thus, they propose a sparse representation of bands with row-sparsity constraint. Besides, a dissimilarity-weighted regularization term is integrated with the self-representation model, to avoid contiguous bands. The problem is solved by the alternating direction method of multipliers, and the representative bands can be chosen. In (Sun et al., 2017), a fast and robust self-representation framework to select a band subset is proposed. It is assumed the separability structure of the spectral bands, thus the problem may be seen as non-negative matrix factorization. After that, an optimizing convex problem is addressed and augmented Lagrangian multipliers are used to select the band subset. In (Zhu et al., 2017), the authors propose a BS framework that can capture the inter-band redundancy through low-rank modeling. Then, by using an affinity matrix and concepts of data quality, the most representative bands are selected. In (Wang et al., 2015), a BS method based on column subset selection is proposed. By means of column subset selection problem, it is possible to select some bands maximizing the volume of the selected subset of columns. The high dimensionality decreases the contrast amongst bands, thus Manhattan distance is used to get a higher quality in the BS process. In (Cao et al., 2016), the authors propose a framework that removes low-discriminating bands that normally need to be discarded manually. Based on the spatial structure of the data set, it is possible to determine which bands have low-discriminating power. Then, a new clustering algorithm is proposed in order to define the optimum number of bands to be selected.

2.2. Data information analysis

Another criterion that can be used in BS strategies is the HSI data information analysis. For example, in (Sui et al., 2015), the authors propose a framework that integrates both the overall accuracy and redundancy. Thus, an optimization problem using adaptive balance parameter is devised to handle the trade-off between the overall accuracy and redundancy. Furthermore, an unsupervised overall accuracy prediction method was adopted. In (Sun et al., 2014), the authors propose a framework that merges the concept of noise-adjusted principal components with maximum determinant of covariance matrix. A new index to measure the HSI quality is also proposed, taking into account signal-to-noise ratios (SNR) and correlation of bands. Based on the new index, the authors...
devise an unsupervised band selection method, which
considers the quality of the data set as selection crite-
rion. It selects bands with both high SNR and low corre-
lation. In (dos Santos et al., 2015), the authors propose
a BS method based on the dissimilarity amongst neigh-
broring bands. They use an intermediary representation
textual notation spectral, which can take advantage of
of a pixel sampling strategy, what ends up improving its ef-
iciency without reducing the selected bands quality. In
(Luo et al., 2017), the authors propose a method based
on information-assisted density peak index. It takes
into account the intraband information entropy into the
local density and intercluster distance to ensure cluster
centers with a high quality. Besides, the channel prox-
imity and band distance are integrated to control the local
density compactness. The bands with top-ranked scores
may get clear global distinction, good local density and
also high informative quality. In (Chang et al., 2017), the
authors formulate the BS as a channel capacity problem.
After constructing a band channel with the original bands.
Then, some bands are selected by Blahut’s algorithm, which
iteratively finds a feature space that provides the
best channel capacity. Thus, neither band prioritization
nor interband decorrelation are required. Two iterative
methods are devised to find the best band subset, which
avoid an exhaustive search.

2.3. Graph theory

Using graph theory, in (Yuan et al., 2017) the au-
authors propose a multigraph determinantal point process
(MDPP). The aim is to capture the structure amongst
bands and find the optimal band subset. For this, multiple
graphs are designed to capture the intrinsic relationship
amongst bands. Besides, the proposed MDPP is used to
model the multiple dependencies in graphs, providing an
efficient search strategy for the BS process.

2.4. Evolutionary computation

Evolutionary computation with optimization have been
largely used by BS methods. For example, in (Xu et al.,
2017), the authors propose an incorporated rank-based
multiobjective band selection approach, to avoid conflict-
ning objective functions, such as Jeffreys-Matusita (JF)
and Bhattacharyya distances. During the processing, the
spectral bands are transformed into binary vectors, whose
elements are subjected to flipping with a certain proba-

ility. In (Gong et al., 2016), the authors propose a frame-
work that handles two conflicting objective functions. One
function is designed to represent the information conten-
tained in the selected bands, by means of entropy. The
other function is set as the number of selected bands.
Both objective functions are optimized simultaneously by
a multiobjective evolutionary algorithm. In (Su et al.,
2014), the authors propose a framework for band selection
which employs two objective functions using JF. During the search
process, the spectral bands are treated as firefly variables.
In (Zhang et al., 2017a), a framework for band selection
based on fuzzy clustering and swarm optimization in pro-
posed. The authors devise a modified fuzzy clustering
method for band selection, whose drawbacks are allevi-
ated by swarm optimization. In (Zhang et al., 2017b), the
authors proposed a BS framework based on memetic al-
gorithms (MA). Firstly, MA is used to select a subset of
spectral bands. Also, a objective function is designed to
select bands considering both bands information and re-
dundancy deduction. The authors claim that this method
is not only computationally faster than exhaustive search
approaches, but also has comparable performances.

2.5. Clustering

Finally, clustering techniques can also be used in band
selection methods. For instance, in (Datta et al., 2012)
the authors propose a framework that removes redun-
dancy amongst bands by means of clustering. Then, from
each cluster one representative band is selected. After
that, the bands are ranked according to their classifica-
tion capabilities. In (Yuan et al., 2016), the authors pro-
pose a framework based on dual clustering that takes
into account the contextual information. For this, a novel
descriptor that reveals the image context is devised, in
order to select the representatives of each cluster, taking
into consideration the mutual effects of each cluster.

3. Proposed Framework

3.1. Definitions

Let \( C^{(i)} \) be a hyperspectral dataset, whose elements
are vectors \( x_i \in \mathbb{R}^{d \times 1} \) that contain spectral signatures,
where \( d \) is the number of bands.

Let \( S \) be the set that contains the selected bands, and
let \( G \) be set with bands highly correlated to the bands
in \( S \). Let \( A \) be the set containing the original spectral bands
\( a_k \), with \( k = 1, 2, ..., d \). Let \( \gamma \) be the number of bands to
be selected.

Let \( f : F \rightarrow t \) be a single-layer neural network,
where \( t = \{0, 1\} \), and \( F \) is the feature space given by
\( A \setminus (S \cup G) \). The input to \( f \) is \( x \) and its output is a scalar
given by

\[
\hat{t} = f(z) = \frac{1}{1 + e^{-z}}. \tag{1}
\]

where \( z = w^T x + b \), where \( w \) and \( b \) are, respectively, the
weights and bias of the neural net.

According to Formula 1, \( \hat{t} \in [0, 1] \), and we adopt the
following criteria to give it a binary value:

- If \( z < 0 \) \( \Rightarrow f < 0.5 \) \( \Rightarrow \hat{t} \leftarrow 0 \),
- If \( z \geq 0 \) \( \Rightarrow f \geq 0.5 \) \( \Rightarrow \hat{t} \leftarrow 1 \).

Thus, the signal of \( z \) determines whether an input
vector is to be assigned to class 0 or 1.

The input data is normalized into \([0, 1]\), consequently
the biggest weights \( w_l \in w \), with \( l = 1, ..., p \), in the hyper-
plane equation

\[
z = x_1^l w_1 + x_2^l w_2 + ... + x_p^l w_p + b \tag{2}
\]

cause a major impact on the signal of \( z \), and, conse-
quently, the estimate \( \hat{t} \), for \( x_i \). In Formula 2, \( p \) represents
the cardinality of the feature space \( F = A \setminus (S \cup G) \).
As for the cost-function of \( f \), we adopt the cross-entropy. The parameters learning is done by means of stochastic gradient descent and back-propagation algorithm (Theodoridis and Koutroumbas, 2008).

Finally, let \( \mathbf{C}_q^{(l)} \) be a partition of \( \mathbf{C}^{(0)} \), where \( l \) is the partition level, and \( \mathbf{C}_q^{(l)} \cup \mathbf{C}_{k}^{(l)} \cup \cdots \cup \mathbf{C}_{q}^{(l)} = \mathbf{C}^{(0)} \) and \( \mathbf{C}_q^{(l)} \cap \mathbf{C}_q^{(l)} = \emptyset, \forall p \neq q \). Depending on the problem, there may be several levels, i.e., \( l = 1, 2, 3, \ldots \), and for each level \( l \) the number of partitions \( g \) is calculated by

\[ g = 2^l. \]

### 3.2. Description

#### 3.2.1. General view

Our method starts with an empty set, that is, \( \mathbf{S} = \emptyset \), to which the bands selected from \( \mathbf{A} \) will be added. Initially, at the first iteration, \( \mathbf{C}^{(0)} \) is clustered by \( k \)-Means into two groups, \( \mathbf{C}^{(1)}_1 \) and \( \mathbf{C}^{(1)}_2 \), using Euclidean distance. After that, a single-layer neural network is used to find a separating hyperplane between those two partitions. Then, two bands are selected and removed from the feature space \( \mathbf{F} \). If more bands are needed, this procedure must be repeated using the just generated clusters.

Since the proposed framework is based on clustering and single-layer neural network, it will be called CSLN. In the sequel, deeper details will be given.

#### 3.2.2. Iterations

CSLN is an iterative BS framework. At each iteration, a two-class classification problem between the clusters generated by \( k \)-Means \( \mathbf{C}^{(0)}_q \) and \( \mathbf{C}^{(0)}_q \) is to be solved by means of the function \( f \). Two bands are selected at each iteration, thus it is necessary to repeat this process until the number of bands \( \gamma \) is reached. These criteria are adopted:

- If \( \gamma \) is even, \( \gamma/2 \) iterations are necessary; or
- If \( \gamma \) is an odd number, we need \( (\gamma + 1)/2 \) iterations. Then, only the first \( \gamma \) selected bands are selected.

#### 3.2.3. Selection of bands

When the training of the neural network ends, it is possible to assess the importance of all \( a \in \mathbf{F} \) by analyzing \( \mathbf{w} \). Every element \( x^l \in \mathbf{x} \) is associated to \( w_l \)—see Figure 1—, for \( l = 1, \ldots, p \), thus the magnitude of \( w_l \) is an indicator for the band \( a_l \). In Formula 2, the largest and the smallest weights are the most important contributors to the signal of \( z \). Consequently, the bands attached to those weights are also considered the most important, thus they are added to the set \( \mathbf{S} \). Then, the feature space \( \mathbf{F} \) is updated by \( \mathbf{A} \setminus (\mathbf{S} \cup \mathbf{G}) \).

Since the dimensionality of the feature space \( \mathbf{F} \) changes after each iteration, the neural network must be trained from scratch at each iteration, because the sizes of \( \mathbf{w} \) and \( \mathbf{b} \) also change.

**Algorithm 1** Proposed band selection framework

1. Input : \( \mathbf{C}^{(0)}, \mathbf{A}, \gamma, \mathbf{S} = \emptyset \) and \( \mathbf{G} = \emptyset \)
2. for \( \tau = 1 : \text{max iterations} \) do
3. Train a single-layer neural network \( f \) to find a separating hyperplane between \( \mathbf{C}^{(l)}_p \) and \( \mathbf{C}^{(l)}_q \), previously clustered by \( k \)-Means
4. Identify the bands \( a_k \in \mathbf{F} \) associated to the largest and smallest \( w \in \mathbf{w} \)
5. \( \mathbf{S} \leftarrow a_k \), and \( \mathbf{G} \leftarrow a_{q_{k}(1)} \)
6. Update \( \mathbf{F} \) by \( \mathbf{A} \setminus (\mathbf{S} \cup \mathbf{G}) \)
7. end for
8. Return : \( \mathbf{S} \)

Figure 2 illustrates the proposed method. Initially, the whole dataset is clustered into two groups by \( k \)-Means. Then, a separating hyperplane between them is calculated by means of a single-layer neural network. This pro-

![Figure 1: An example of the single-layer neural network used in this thesis. This architecture permits that each band \( \mathbf{x}^i \) be linked to only one weight \( w_i \).](image-url)
cess is repeated until the previously determined quantity of bands is selected.

4. Results

The results of the proposed framework are shown in this Section. We compare our results with other six band selection approaches by taking into account the accuracy of supervised classifiers.

4.1. Datasets and classifiers

In this paper, we use two hyperspectral images, which are

- **Indian Pines** : It consists of 224 spectral reflectance bands in the 0.4-2.5 µm wavelength range. There are 16 classes.
- **Pavia University** : The Pavia University image has 103 spectral bands, and 9 classes.

For the Indian Pines dataset, we use Classification and Regression Trees (CART) and k-Nearest Neighbors.

For the Pavia University image, we use KNN, CART and Support Vector Machine (SVM) (Theodoridis and Koutroumbas, 2008).

All the classifiers are run in MATLAB. For KNN, we use the fitcknn command, k = 3, in all experiments, for a fair comparison. For CART, the command fitctree is used, and to run SVM for multiple classes, we use fitcecoc, with polynomial kernel. All the commands above belong to the Statistics and Machine Learning toolbox.

The proposed BS method is also implemented in MATLAB. We use the trainSoftmaxLayer, from Neural Network Toolbox, for single-layer neural network, with 2000 training epochs. We emphasize that normally the training phase stopped before the 2000th training epoch, so bigger training epochs quantities were not tested. As for the k-Means algorithm, we use kmeans, from the Statistics and Machine Learning toolbox.

The classifiers input data are the images with the selected bands. Moreover, the number of bands selected by our framework are for comparison purposes. Thus, it does not mean they are the best quantity for any given task.

For the classification step, each dataset is divided in two subsets. The first one is used for the classifier training, using 70% of the data. The second subset has the remaining 30%, and is used during the test phase of the classifier. The results shown in Section 4.4 are calculated based on this second data subset.

4.2. Competitors

The performance of the proposed CSLN framework is compared with six other band selection methods. Four of them are used with the Indian Pines image:

- This method uses both ranking and clustering for band selection (Datta et al., 2015), and we will call it CR;
- This competitor relies on information divergence, and it will be called ID (Chang and Wang, 2006);
- This framework is also clustering-based (Martinez-Uso et al., 2007), and it will be referred to as Walud1; and
- This method resorts to band elimination with partitioned image correlation (Datta et al., 2014), and it will be referred to as EM.

For the Pavia University image, there are two competitors:

- It is a framework that handles two conflicting objective functions. One function is designed to represent the information contained in the selected bands, by means of entropy (Gong et al., 2016). It will be called MOBS;
- This framework constructs a band channel with the original bands. Then, some bands are selected by means of Blahut’s algorithm, which iteratively finds a feature space that provides the best channel capacity (Chang et al., 2017). This competitor will be referred to as CC.

As already stated in Section 3.2.1, the proposed BS algorithm will be called CSLN.

4.3. Selected bands

The bands selected by the CSLN method are shown in Table 4.3. For the Indian Pines dataset, we have only the first 18 best-ranked bands of the competitors, consequently, the analyses of results are restricted to this quantity of bands. For the Pavia University image, 21 bands are selected for the same reason.

The bands in Table 4.3 are displayed according to the order they were selected. For instance, at the first iteration, the bands 2 and 42 were selected for the Indian Pines image.

---

FIGURE 3: The Indian Pines dataset under the KNN classification.

The comparison of results is made taking into account different quantities $\gamma$ of selected bands, that is, $\gamma_s = s \times 3$, with $s = 1, 2, 3, 4, 5, 6$, for Indian Pines. For example, for $\gamma_6 = 6$, the first six bands of Table 4.3 are used. For the Pavia University dataset, $s = 1, 2, 3, 4, 5, 6, 7$.

<table>
<thead>
<tr>
<th>Selected bands</th>
<th>for Indian Pines</th>
<th>Selected bands</th>
<th>for Pavia University</th>
</tr>
</thead>
<tbody>
<tr>
<td>2, 42, 6, 39, 22, 58, 25, 62, 71, 101, 94, 151, 111, 203, 156, 183, 171, 215.</td>
<td>69, 1, 68, 3, 92, 6, 77, 18, 101, 24, 99, 51, 14, 74, 9, 75, 29, 97, 95, 8, 103.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE 1: The selected bands according to the order of selection by the proposed method.

4.4. Results comparison

All the classification results shown in this paper are the mean values over ten runs.

The results for the Indian Pines image are shown in Table 4.4. Using KNN, the proposed method CSLN has the best results using 3, 6 and 9 bands. This fact is illustrated in Figure 3.

The results achieved by the CART classifier using Indian Pines are also shown in Table 4.4. The proposed method has the best results with 3 and 9 bands. Figure 4 gives a visual idea of the results.

For the Pavia University dataset, the results are given in Table 4.4. Using the KNN classifier, the CSLN method achieves the best results using 3, 6, 9, 12 and 15 bands. This is shown in Figure 5.

For the CART classifier, the proposed method has the best results with 3, 6, 9 and 12 bands. In Figure 6 it is possible to have a visual perspective.

With the SVM classifier, our framework has the best results with 3, 6, 9, 12 and 15 bands, which is shown in Figure 7.

4.4.1. Visual inspection of the selected bands

The spectral signatures of the different classes give us an idea of the features—or bands—that provide a good
## Table 2: Classification results for Indian Pines.

<table>
<thead>
<tr>
<th>Method</th>
<th>3 bands</th>
<th>6 bands</th>
<th>9 bands</th>
<th>12 bands</th>
<th>15 bands</th>
<th>18 bands</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSLN</td>
<td>86.66%</td>
<td>90.63%</td>
<td>91.32%</td>
<td>92.11%</td>
<td>92.64%</td>
<td>91.83%</td>
</tr>
<tr>
<td>MOBS</td>
<td>70.30%</td>
<td>77.26%</td>
<td>87.68%</td>
<td>90.19%</td>
<td>91.15%</td>
<td>92.73%</td>
</tr>
<tr>
<td>CC</td>
<td>85.98%</td>
<td>85.98%</td>
<td>86.32%</td>
<td>87.14%</td>
<td>87.91%</td>
<td>90.37%</td>
</tr>
</tbody>
</table>

## Table 3: Classification results for Pavia University.

<table>
<thead>
<tr>
<th>Method</th>
<th>3 bands</th>
<th>6 bands</th>
<th>9 bands</th>
<th>12 bands</th>
<th>15 bands</th>
<th>18 bands</th>
</tr>
</thead>
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<td>87.14%</td>
<td>87.91%</td>
<td>90.37%</td>
</tr>
</tbody>
</table>
FIGURE 7: The Pavia University dataset under SVM classification.

FIGURE 8: Mean spectral signature values of the Indian Pines image classes. The vertical lines indicate the location of the first 6 bands selected by the proposed CSLN method.

FIGURE 9: Mean spectral signature values of the Pavia University image classes. The vertical lines indicate the location of the first 6 bands selected by the proposed CSLN method.

FIGURE 10: Two Indian Pines dataset clusters. The straight line is calculated by a single-layer neural network.

4.4.2. Considerations about the single-layer neural net choice

As already stated in Section 3.2.3, our rationale for the band selection is based on Formula 2, which, in turn, is the separating hyperplane calculated by the single-layer neural network used in this chapter. If the neural net does not converge to a good local minimum, or if its architecture is not appropriate for the problem at hand, no conclusion based on Formula 2 would be reliable.

FIGURES 7 and 9 show the mean spectral signatures of the classes present in Indian Pines and Pavia University datasets, respectively. In order to avoid excessive visual information, the location of only the first 6 selected bands is displayed, in vertical lines.

We notice that in both cases the selected bands fall in regions where the spectral signatures are far from one another. It denotes that our BS framework proposed in this chapter is capable of selecting appropriate spectral bands.

4.5. Remarks about the results

4.5.1. KNN versus CART

For the Indian Pines image, KNN results are, in general, superior than that of CART: 73.26% and 63.13%, respectively. This may be attributed to the fact that CART...
FIGURE 11: Two clusters from the Pavia University image. The straight line that separates the groups is calculated by a single-layer neural network.

FIGURE 12: Mean results of the three classifiers used for the Pavia University image.

splits the feature space into regions that correspond to the classes. Therefore, if $x_i$ is found in a region corresponding to a class $\alpha$, for example, it will be classified as $\alpha$, even if it belongs to class $\beta$. Whereas, in this same situation, KNN would analyze the $k$ nearest neighbors of $x_i$ before assigning it a label. Consequently, KNN outperforms CART when the class boundaries are highly nonlinear.

4.5.2. KNN, CART and SVM

Concerning the Pavia University image, the mean results for the KNN, CART and SVM are, respectively, 88.30%, 78.31% and 85.69%. This shows a slight superiority of KNN in relation to SVM, what is somehow unexpected in high dimensional feature spaces, as shown in Figure 12. It is worth mentioning that our objective in this thesis is the classification comparison amongst different BS methods, and not the best attainable classification result. For this, further studies on the classifiers hyperparameters would be necessary.

4.5.3. Band selection methods

As for the band selection methods, using the Indian Pines image, the proposed BS framework achieves the best results in 5 out of 12 experiments, whereas the competitors have $1/12, 2/12, 1/12$ and $0/12$. For the Pavia University image, our method gets $14/21$, and the competitors $7/21$ and $0/21$. The CSLN framework not only gets superior results than its competitors, but it is also easily implementable. Thus, one can conclude that it is a good method for band selection.

5. Conclusion

The spectral information provided by HSIs allow for a rich characterization of objects in the scene. However, the large amount of data can also bring problems in terms of processing and storage. Furthermore, features spaces with high dimensions can cause the curse of dimensionality. Thus, we proposed a band selection method to decrease the dataset dimensionality.

The proposed unsupervised BS framework is based on $k$-Means clustering and single-layer neural network. It begins by splitting the whole dataset into two clusters. After that, a single-layer neural network is used to calculate a separating hyperplane between the two groups. The bands associated to the biggest and smallest hyperplane coefficients are selected. After that, one needs to repeat this procedure using the generated clusters until the desired number of bands is achieved.

According to the the results, we saw that the proposed CSLN method outperformed its competitors in both images analyzed.

As for the future works, we will investigate other clustering algorithms and binary classifiers to check their performance in the proposed framework.

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Références


