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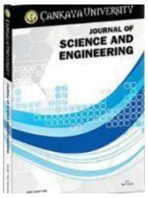

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Dominant Sets Based Pre-Feature Selection Method for Hyperspectral Data

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Keywords

Hyperspectral image processing,
Dominant sets,
Band selection,
Dimension reduction,
Feature selection.

Abstract

Hyperspectral Data has a large volume compared to panchromatic and RGB data. This large volume can lead to processing, storage, and transmission problems. Therefore, it is crucial to decrease the size of the hyperspectral data for practical applications. Feature selection can be used in order to get rid of large data size problems. In this paper, a pre-band selection framework is presented to reduce the data size and to reduce the complexity of a well-known band selection method in hyperspectral imagery: Sequential Forward Selection (SFS). The proposed pre-band selection method is based on "dominant sets". Clustering performance of each spectral band is evaluated, and a reduced set of spectral bands is formed based on the clustering performances. SFS is applied to this reduced hyperspectral data. The aim of the study is to reduce the computational complexity of SFS by applying a dominant set based pre band selection method. Besides reducing the computational complexity of SFS method, results on Pavia and Indian Pines datasets show that the proposed pre-feature selection method performs slightly better than the state-of-the-art feature selection methods in terms of classification accuracy.

1. Introduction

Hyperspectral imaging provides more information that can be gathered in the detection of materials and objects as compared to multispectral imaging. Hyperspectral imagery has hundreds of narrow contiguous bands. This large data size has processing, storage, and transmission drawbacks. Large data volume requires large processing time, bigger data storage capacity, and higher transmission rates. To get rid of the large data size problems, dimension reduction techniques are applied to reduce the hyperspectral data size.

Dimension reduction techniques can be divided into two main groups: feature extraction and feature selection. Feature selection methods are preferred since a subset of the original input data is selected based on a set of criteria and the original data is not deteriorated. On the other hand, feature extraction methods transform data into a different space and the data is altered.

A short survey of research and development for hyperspectral remote sensing applications including band selection, feature extraction and classification techniques is presented in [1]. A feature extraction method using multidimensional spectral regression whitening is proposed in [2], and in this method, the data passes through a number of steps involving, entropy rate segmentation, spectral regression whitening, classification, and voting. In [3], empirical mode decomposition-based feature selection method is applied and both spatial and spectral information are extracted. It is crucial to combine spectral and spatial information for hyperspectral imagery since

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hyperspectral imagery has the advantage of containing both information compared to single band monochrome data.

In [4], the authors merge I-ReliefF and cross-scene algorithms and introduce a cross-domain I-ReliefF algorithm which shows better performance than that of the I-ReliefF and cross-scene algorithms. In [5], making use of the spatial information, the authors proposed patch-based and tensor patch-based, approaches to be utilized by graph-based dimensionality reduction methods. The proposed methods are called weight-modified tensor locality preserving projections and weight-modified tensor neighborhood preserving. It is reported in [5] that the proposed approaches outperform the up-to-date algorithms. In hyperspectral imaging, spectral and spatial information can be concatenated to obtain longer feature vectors and in sequel dimensionality reduction can be performed, and finally, classification can be achieved. However, such a rough approach to obtain the longer feature vectors faces many weaknesses due to the inappropriate use of the different data vectors in a longer vector. To alleviate the weak points of vector concatenation, in [6] authors proposed a smarter approach to benefit from different types of feature vectors in an intellectual manner. In [6], authors transform spectral-spatial feature to another feature space and the most significant original features of data vector are used for classification.

Band selection methods are the most popular feature selection methods that select the most valuable bands and remove the redundant bands based on a set of criteria [7, 8, 9].

The hyperspectral band selection technique can be ranking [10, 11] or clustering-based [12]. Ranking-based methods are utilized for detecting the most informative and distinctive bands. However, there is a drawback that ranking based methods can select redundant bands since correlation among selected bands is not considered in this method.

Sequential Forward Selection (SFS) Method is a ranking based band selection method applied to hyperspectral imagery [13]. SFS method is a sub-optimum feature selection method. [14] The first step of SFS is to find the best single band based on the defined criteria. Then the next band that gives the best performance with the first selected band is selected. This procedure continues until no additive spectral band increases the performance of the current set of spectral bands. SFS is computationally complex. Suppose there are M bands selected over N bands by SFS. The computational complexity is $N!/M!$.
Unlike ranking based methods, clustering-based methods take correlation among the bands into account. These methods firstly cluster bands based on determined criteria and then select one band from each cluster as a representative one.

Graph-based representations gain popularity for solving clustering problems in pattern recognition. There are several advantages in using graphs instead of feature vectors for object representation [15]. Shi and Malik introduced normalized cuts method, which was based on a generalized eigenvalue problem to obtain graph partitions according to normalized cuts criterion [16]. On the other hand, Pavan and Pelillo proposed a dominant sets method (DSM) in which a graph-theoretic definition of a cluster was introduced [17]. The DSM is closely related to the maximum clique problem in graphs as well. Pavan and Pelillo [17] demonstrated the relation between DSM and maximum clique when weighted undirected graph is induced to un-weighted undirected graph. In the literature, the dominant set technique is utilized to solve distinct clustering problems [18, 19]. The main idea of these methods is to obtain a graph-based representation of a pattern recognition problem by mapping the graph elements with vertices and mapping the relationship of the graph elements with weighted edges. Therefore, the problem is reduced to solving a graph-based optimization problem. In this paper, we propose a dominant sets based pre-feature selection method to be used before SFS band selection. Therefore, our complete band selection method combines clustering selection technique with a ranking selection technique.

In [20], a method that evaluates the clustering performance of spectral bands is proposed. This method is clustering each spectral band based on "dominant sets" technique and it evaluates the clustering performance of each band. The proposed method is time efficient since it works on a small set of training data instead of the whole hyperspectral data. In [20], "dominant sets" technique is first applied to hyperspectral image processing as a clustering method.

Hyperspectral image classification is an important application in agriculture, forestry, geology, ecological monitoring, and disaster monitoring [21]. In a typical real-life scenario, a few spectral bands are required to discriminate the given number of classes on a hyperspectral data. The main challenge is to reduce the data by applying feature selection methods with low computational complexity. Therefore, it is a good idea to combine DSM approach with sub-optimum band selection method SFS to get high classification performance without increasing the computational complexity. In this paper, we propose a pre-feature selection method based on dominant sets approach before SFS i.e., dominant sets based pre feature selection method combined with SFS (DSM-SFS) in order to overcome the above-mentioned problem.

2. The Proposed Approach

DSM-SFS method has two main stages. The first stage, dominant sets-based preselection method (DSM), is a graph-based clustering band selection method. It aims to cluster the bands by dominant sets approach and eliminates some of the spectral bands that do not increase the classification accuracy before performing SFS. The second stage is SFS. SFS is applied to a reduced set of spectral bands to find the best performing spectral bands.

In [20], DSM is utilized, and clustering performances of each spectral band is calculated. Fundamentals of dominant sets method is described in this study. DSM computes the discrimination performances of the bands for determined classes in a specific application in order to utilize the result as a band clustering criterion. In DSM, the pixels in each band are clustered into groups. These clusters are matched with known classes by using the ground truth and the clustering performance of each band is evaluated for each class. The aim is to eliminate some of the spectral bands that do not increase the classification accuracy before performing SFS. Therefore, redundancy and useless spectral bands for the defined classes will be omitted.

DSM-SFS band selection method is explained in Figure 1.

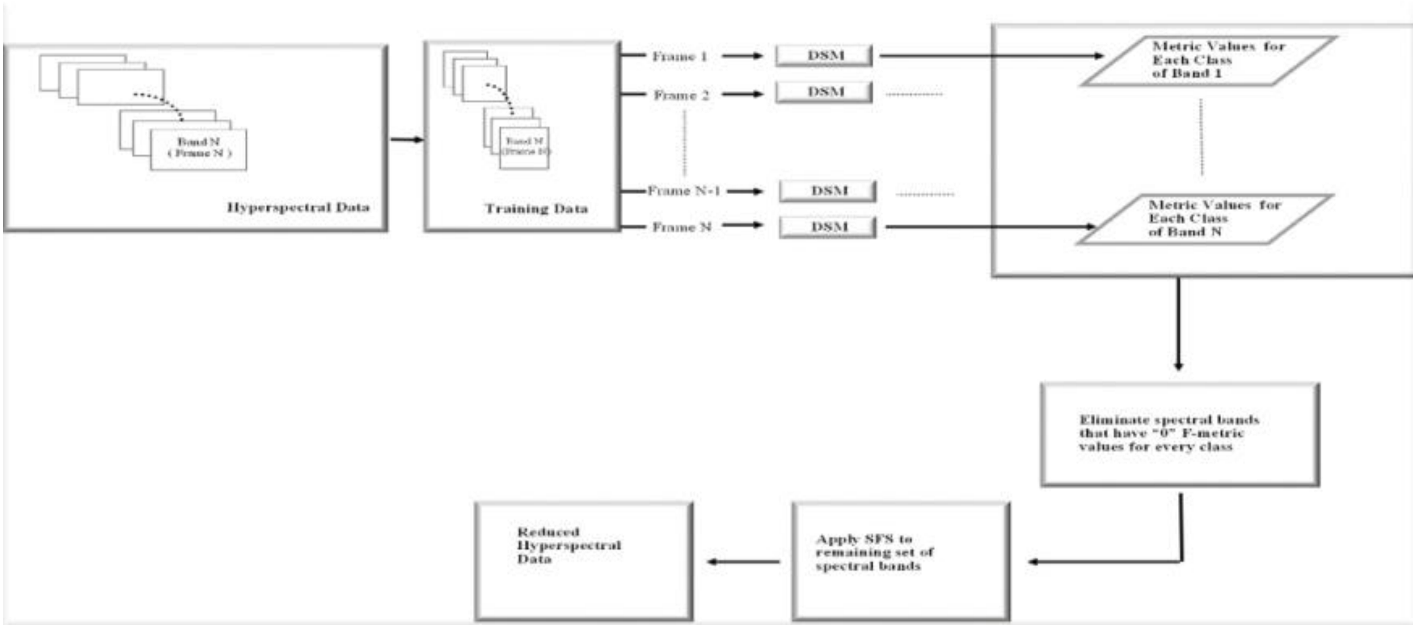

Figure 1. Salinas A ground truth including 6 classes and unclassified regions.

The main steps of the proposed DSM-SFS method are:
1. Select a small size training data including samples from the classes under interest. The whole band selection algorithm is performed on this training data.
2. DSM is applied at each frame that belongs to a specific band for clustering.
3. Metric values of each frame are evaluated for each class, and a metric associated with each frame is evaluated at each class and average metrics for all the classes are calculated.
4. Perform the unsharp masking filter on metric values to derive an unsharp and less blurry signal by creating a mask of the original signal. Therefore, filtered metric matrix for each spectral band is formed.
5. Eliminate the spectral bands that have zero metric values for every class under concern. Remaining spectral bands forms the selected set of bands.
6. SFS is applied to selected set of bands on a training data.

3. Dominant Sets-Based SFS (DSM-SFS) Pre Feature Selection Method Combined With SFS (DSM-SFS)

This feature selection method proposes a selected set of bands for discriminating the classes under concern. In order to achieve this, a small part of the hyperspectral image that contains sufficient samples for the interested classes is selected. The DSM-SFS will be performed on the selected part of the whole image.

F-measure metric [15] is used to quantify the classification performance of bands. In order to evaluate the discrimination performance of bands, pixels in each frame that belongs to a specific band are clustered by DSM. Then, the clustered pixels are classified by the ground truth. The cluster is appointed to the class that has the highest number of member pixels in the cluster. As a result, each band frame is classified. Classification performance is evaluated using F-measure metric [15].

Let H_f be the $L \times M \times N$ hyperspectral image i.e., the hyperspectral cube has L bands, M pixels in the image frame row, and N pixels in image frame column. Let H be the partition of H_f including sufficient samples of the classes under concern. That is, H is also a hyperspectral image having L bands and K number of pixels such that $K < M \times N$. Therefore, H can be expressed as:
$H = \{H_l\}_{l=1}^{L}$
where H_l is the l^{th} band of the hyperspectral image and it is a K pixel image frame.

In this stage, each frame that belongs to a specific band i.e., H_l, is subjected to DSM to form the clusters. The first step is to form the similarity matrices for each band. Let W_l be the $K \times K$ similarity matrix for the l^{th} band and $Wl(i,j)$ is the element of the similarity matrix that represents the similarity between the i^{th} and j^{th} pixels, $1 \leq i,j \leq K$.

In order to form the similarity matrix, it is required to have a similarity measurement function. It is determined that this function is related to both spatial and spectral information. Therefore, $W_l(i,j)$ is defined as:

$$W_l(i,j) = e^{-C_d {d_{ij}}^2} e^{-C_s|r_l(i)-r_l(j)|} \tag{1}$$

where C_d and C_s are spatial and spectral information parameters respectively. Once these parameters are determined they are used for every $W_l(i,j)$. $r_l(i)$ is the reflectance value of i^{th} pixel for the l^{th} band. Indeed, $r_l(i)$ is an element in H_l. The spatial distance in the image frame between pixels i and pixel j is represented as d_{ij}.

After forming the similarity matrix, the dominant set is iteratively calculated [20]. The threshold Th defines the number of iterations. The remaining part of the first stage of the proposed method is given in the following steps:

Step-1. The initial value of x_l is a K size array consisting of all ones. It means that initially all pixels of the l^{th} band is in the dominant set.

Step-2. Calculate the dominant set.

Step-3. If $|x_l(t+1) - x_l(t)| > Th$, then $x_l(t) = x_l(t+1)$ and go to *Step*-2. Otherwise, go to *Step*-4.

Step-4. The dominant set is finalized. The dominant set elements constitute the cluster. This cluster is assigned to the proper class by using the ground truth. The maximum number of cluster pixels that are affiliated to the same class defines the class of the cluster. Therefore, the pixels in the dominant set are classified.

Step-5. The classified pixels are extracted from the image and the similarity matrix elements related to these pixels are eliminated from the similarity matrix W_l.

Step-6. If there are unclassified pixels, then form the array x_l with a size equal to the number of unclassified pixels consisting of all ones and go to *Step-2*. Otherwise, go to *Step-7*.

After performing the iterative algorithm, all the pixels are classified. The next step is to evaluate the performance of bands for each class with a metric. For the evaluation process, it is important to succeed in both clustering the pixels that belong to the same class in the same cluster and preventing from the mismatch of the cluster pixels with incorrect classes. Therefore, F-measure metric [22] is selected to evaluate the performances since it takes not only the detection but also the false alarm into account. It measures the quality of the detected clusters and its value ranges from 0 to 1. $F = 1$ indicates a perfect result.

F is defined as

$$F = \frac{1}{Z} \sum_{C_i \in GT} |C_i| \max_{c_j \in DT} \{f(C_i, C_j)\} \tag{2}$$

Where

$$f(C_i, C_j) = \frac{2 \times \mathrm{Re}(C_i, C_j) \times \mathrm{Pr}(C_i, C_j)}{\mathrm{Re}(C_i, C_j) + \mathrm{Pr}(C_i, C_j)}, \tag{3}$$

GT is the ground truth and DT is the dominant set, and Z is calculated as

$$Z = \sum_{C_i \in GT} |C_i| \,. \tag{4}$$

Recall (Re) and *precision* (Pr) functions are defined as:

$$\mathrm{Re}(C_i, C_j) = \frac{|C_i \cap C_j|}{|C_i|} \tag{5}$$

$$\mathrm{Pr}(C_i, C_j) = \frac{|C_i \cap C_j|}{|C_j|} \tag{6}$$

Step-7. As described in *Step-4*, F metric is calculated after the clusters are assigned to the proper class. Calculate the F metric of the l^{th} band for each class by using the equation

$$F_l(i) = \frac{1}{Z} \sum_{c_i \in GT, c_j \in DT} |C_i| \times f(C_i, C_j)$$

for $1 \leq i \leq P$ where P is the number of classes in the ground truth.

Step-8. F_l is l^{th} band performance for each class and each element of this array $F_l(i)$ refers to a distinct class in the ground truth.
Steps 1 to 8 are applied to each band of the hyperspectral cube. Therefore, the performances of the hyperspectral bands are evaluated separately.

Step-9. Perform the unsharp masking filter on F metric values.

$F_{l,new}(i) = h_{unsh} \times F_l(i)$, for $1 \leq i \leq P$ where P is the number of classes under concern.

$$h_{unsh}[n] = \begin{cases} 1, & if\ x[n] > \left(\frac{1}{L_u} \sum_{m=-\frac{L_u-1}{2}}^{\frac{L_u-1}{2}} x[n+m] \right) + std_{L_u}(x[n]) \\ 0, & otherwise \end{cases}$$

L_u is the length of the unsharp masking filter and std_{L_u} is the local standard deviation within L_u length. Actually, a local threshold is defined for each sample of the signal based on its neighbor samples. This threshold equals to the sum of mean and standard deviation values within the filter length. This unsharp masking filter is applied to F metric values of spectral bands for each class. Therefore, this process removes the sharp and noisy signals and forms the most valuable spectral bands for each class. Then the valuable bands for each class are merged to form the spectral bands set to be given as an input to SFS.

Step-10. For $F_{l,new}(i)$, eliminate the spectral bands that have zero F metric values for every classes under concern. Remaining spectral bands forms the selected set of bands.

Step-11. SFS is applied to selected set of bands on the training data.

4. Data Set and Performance Evaluation

4.1. Data Set and Ground-truths

Salinas and Pavia scenes [23] are employed in our work. Salinas Data has 224 spectral bands and Pavia Data has 115 spectral bands. However, there are unused noisy bands. After noisy band elimination 200 spectral bands are used for Salinas Data whereas 103 spectral bands are used for Pavia Data. As described earlier, DSM-SFS is performed on a small partition of the whole hyperspectral image that contains sufficient samples for the interested classes.
Salinas A data includes six classes. Salinas A data is the subset of the Salinas data. Salinas A is approximately 5% of Salinas data when removing the unclassified regions. Salinas data includes 10 more classes but these class samples are signed as unclassified since they are not under concern. The ground truth of Salinas A is shown in Figure 2.

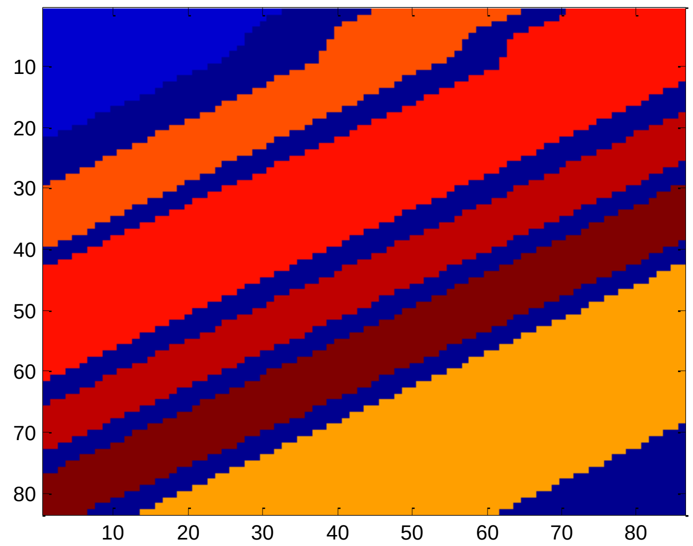

Figure 2. Salinas A ground truth including 6 classes and unclassified regions.

A partition from Pavia Data is selected as a training set. A partition includes trees, bitumen, tiles, meadows, bare soil, and water classes are selected from the Pavia data. This partition is approximately 0.3% of the full Pavia data when removing the unclassified regions. Selected part of Pavia data is shown in Figure 3.

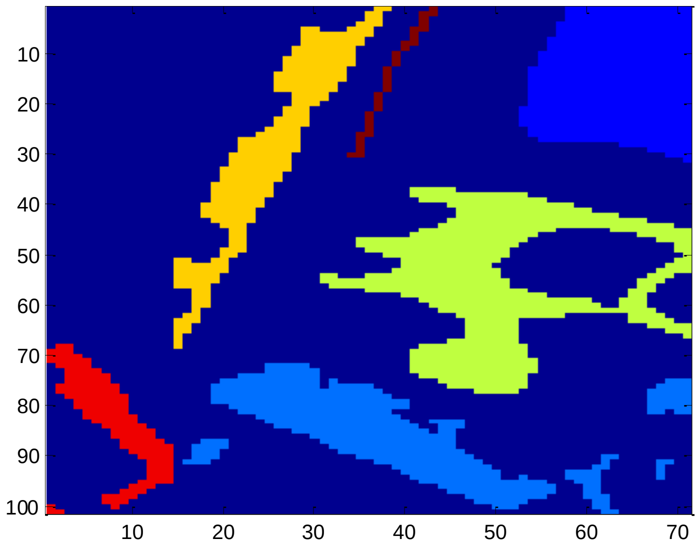

Figure 3. Ground truth of Pavia Data selected partition including 6 classes and unclassified regions.

4.2. Performance Evaluation

DSM-SFS is performed on the two distinct hyperspectral data as mentioned in the previous section. While implementing the DSM-SFS, there are three parameters to determine. Two of them are for the C_d and C_s. These parameters are found iteratively by using the red edge band in Salinas data as 0.3 and 0.01 for the spatial and spectral parameters respectively. For Indian Pines data, spatial parameter remains constant and spectral parameter is multiplied by the ratio of the radiance mean values between the performed data and the Indian Pines data. The remaining parameter unsharp masking filter length L_u is taken as 5.

DSM-SFS takes only the samples of the classes under concern into account. Once DSM-SFS is performed on small partition of the whole hyperspectral data and valuable bands are selected, a new hyperspectral image that includes all the samples but contains only the selected bands is formed. SVM is utilized to evaluate the classification performance of the proposed feature selection method in this section. The classification performance of the method is compared with that of Sequential Forward Selection (SFS) and Correlation Band Selection (CBS) [14]. In order to realize feature selection, the proposed method, SFS, and CBS work on a small set of data. SFS is a suboptimum band selection method that is used in many studies recently. CBS is a simple method that realizes the band selection by considering the correlation among bands. Most uncorrelated bands are selected by CBS. For fair evaluation, the number of selected bands of CBS is equalized to the number of selected bands of DSM-SFS. On the other hand, since SFS is an iterative suboptimum method the selected bands of SFS are accepted as they are. Classification Accuracy [24] vs Number of Training Set performances are analyzed for three band selection methods. Number of training set value defines the number of training samples selected for each class. SVM is performed for different number of training sets, and classification accuracy is calculated for 20 times for the same training set number to get the average value. Training set for SVM is randomly selected and includes samples from each class. Training data set and testing data set are different, i.e. cross validation is implemented. While comparing the performances of the three band selection methods with SVM, training set for SVM is randomly selected, and the same training set is used for all band selection methods.

5. Results

DSM-SFS, CBS, and SFS performances for the Salinas data are shown in Figure 4. It is observed that DSM-SFS performance is slightly larger than that of SFS performance. CBS performance is lower than the others especially for small numbers of training sets.

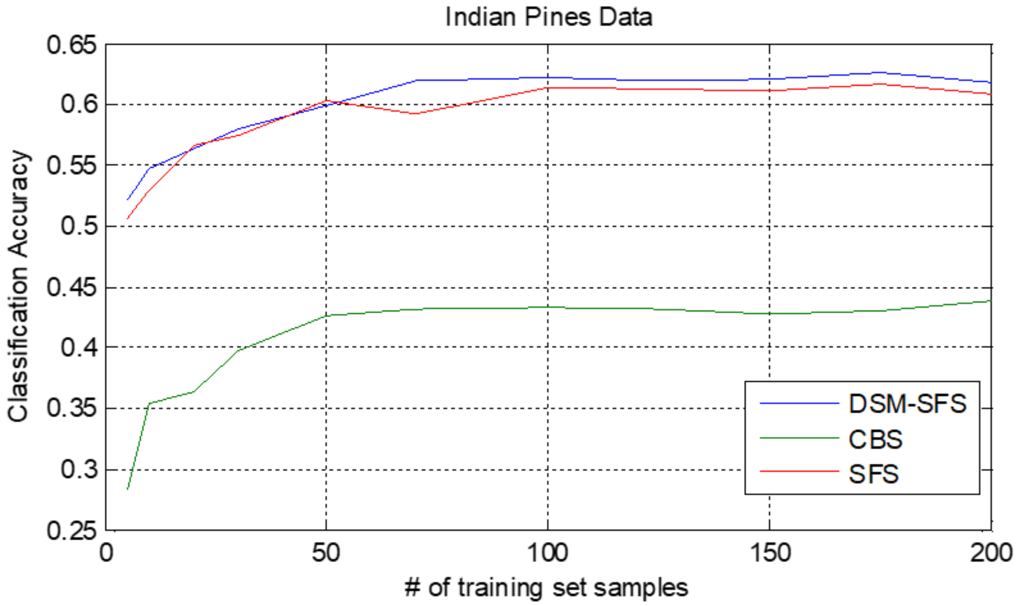

Figure 4. Classification Accuracy vs Number of SVM training set samples performances of DSM-SFS, CBS, and SFS for Indian Pines Data.

DSM-SFS, SFS, and CBS performances for the Indian Pines data are shown in Figure 22. It is observed that DSM-SFS performance and SFS performance are almost the same for small number of training set samples. On the other hand, DSM-SFS performance is larger than that of SFS when the number of training set samples increases. CBS performance is lower than the others.

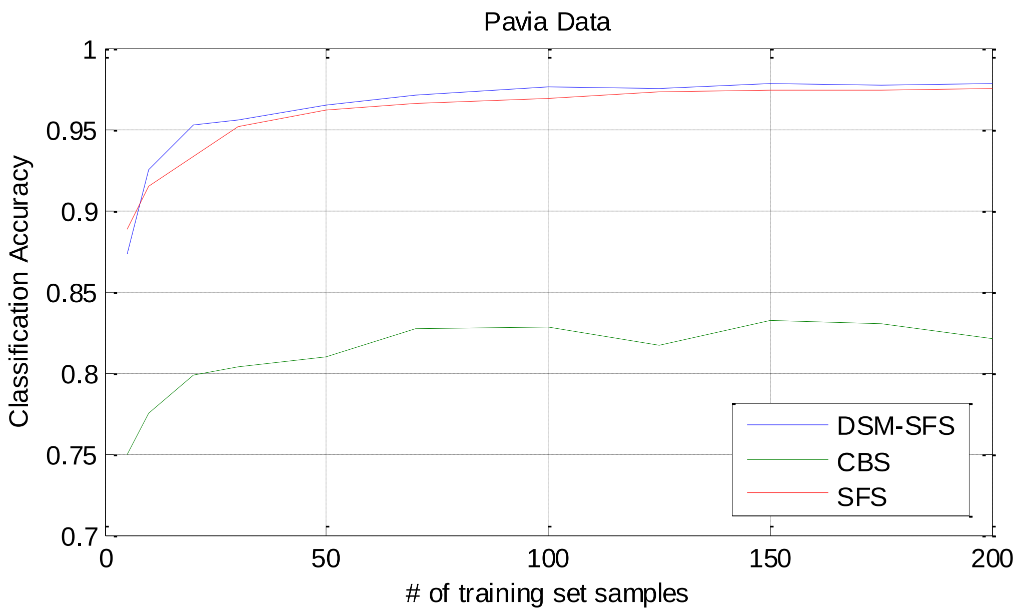

Figure 5. Classification Accuracy vs Number of SVM training set samples performances of DSM-SFS, CBS, and SFS for Pavia Data.

DSM-SFS is proposed for a general set of selected bands for the classes under concern with high classification accuracies. Moreover, CBS and SFS is time consuming since they perform iterative steps to find out the selected bands. In addition to this, the classification method SVM is run for each iteration when SFS is performed.

6. Conclusions

In this paper, we propose novel methods to decrease the large data size of *Hyperspectral imagery* which creates significant latency for communication systems. The proposed feature selection method DSM-SFS performs on a small size of the entire data that includes samples from classes under concern. The performance evaluation of DSM-SFS indicates that the proposed set of selected bands by DSM-SFS can be used to discriminate the classes under concern even for another region that contains not only the same classes but also contains other distinct classes. Therefore, DSM-SFS is a general framework that can define required bands for classification. When compared to the other feature selection methods mentioned in this study such as CBS and SFS, DSM-SFS has higher classification performance. Moreover, DSM-SFS is time efficient since it performs on small size of data and it does not require to calculate classification accuracy iteratively in order to realize feature selection.

SFS works on the whole spectral bands set. In the first step of DSM-SFS the spectral bands are clustered by dominant sets approach and some of the spectral bands that do not increase the classification accuracy are eliminated before performing SFS. The classification performance of DSM-SFS is greater than SFS based on our Monte Carlo simulations mentioned above. Therefore, eliminating the spectral bands that decreases the classification accuracy before implementing SFS can increase the classification performance of SFS.

DSM and unsharp masking filter eliminate some useless bands to decrease the computational complexity of the SFS method. Therefore, DSM-SFS can be preferred instead of SFS since it increases the classification performance slightly and it decreases number of iterations of SFS.

Declaration of Competing Interest

The authors declare that there is no competing financial interests or personal relationships that influence the work in this paper.

Authorship Contribution Statement

Onur Haliloğlu: Methodology, Conceptualization, Implementation, Writing,
Orhan Gazi: Supervision, Reviewing

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