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A survey of band selection techniques for hyperspectral image classification

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Hyperspectral images usually contain hundreds of contiguous spectral bands, which can precisely discriminate the various spectrally similar classes. However, such high-dimensional data also contain highly correlated and irrelevant information, leading to the curse of dimensionality (also called the Hughes phenomenon). It is necessary to reduce these bands before further analysis, such as land cover classification and target detection. Band selection is an effective way to reduce the size of hyperspectral data and to overcome the curse of the dimensionality problem in ground object classification. Focusing on the classification task, this article provides an extensive and comprehensive survey on band selection techniques describing the categorisation of methods, methodology used, different searching approaches and various technical difficulties, as well as their performances. Our purpose is to highlight the progress attained in band selection techniques for hyperspectral image classification and to identify possible avenues for future work, in order to achieve better performance in real-time operation.

Keywords: hyperspectral image, dimensionality reduction, band selection, classification

Introduction

The hyperspectral imaging technology discussed here captures a scene by using various imaging spectrometer sensors [e.g. Airborne Visible Infrared Imaging Spectrometer (AVIRIS), EO-1 Hyperion, Reflective Optical System Imaging Spectrometer (ROSIS) and HyMap] over wavelengths ranging from the visible to the near infrared (VNIR). This range offers detailed spectral information about ground objects in several continuous spectral bands (from tens to several hundreds).[1] Because of their high spectral resolution, hyperspectral images offer a very high discrimination ability between similar ground cover objects.[2] However, the large number of bands brings the curse of dimensionality, which diminishes the discriminating ability of the hyperspectral data as the dimensionality rises with fewer labelled training samples.[3–5] This problem is also referred to as the "Hughes phenomenon".[6] Furthermore, the high dimensionality of the hyperspectral image also carries noisy and redundant information, which increases the computational complexity of the data processing. More importantly, while the data of the complete set of hundreds of spectral bands provide opportunities for a wide range

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of applications, they are not designed for any particular problem. Each band may or may not reveal unique absorption features of the materials of interest in a given problem. Thus, a given band can be a useful feature for one problem, but not for another. Therefore, the original hyperspectral bands are essentially candidate features for a specific application. Dimensionality reduction is an essential task in reducing the number of bands or transforming the data from its original space to a lower-dimensional data space, whilst preserving the desired information from the original data.[7,8]

In general, there are two approaches to reducing the dimensionality of hyperspectral data: feature extraction and band (also called feature) selection. Feature extraction approaches transform original feature space into new feature space, which loses the physical significance of the bands but preserves more discriminative information needed for further analysis.[9–20] In the band selection method, a set of informative bands are selected according to criteria such as information-theoretical approaches (e.g. mutual information, divergence, transformed divergence), distance measures (e.g. Euclidian distance, Bhattacharyya distance, Jeffries–Matusita distance) and searching strategies (e.g. forward selection, backward selection), where the significant physical characteristics of the original spectral bands can be preserved.[21–25] As band selection methods preserve the physical characteristics of the original spectral bands, they are preferred over feature extraction methods. In this review article, the focus is on band selection techniques due to their excellence in practice, including a survey of the approaches suggested by researchers in the past along with their pros and cons.

This article provides a summary of various intensive studies addressing band selection approaches for hyperspectral image classification and indicates possible guidelines for future research. The remaining part of the paper is organised into sections providing a brief overview of the band selection process, classification methods that use spectral information only and a summary of the literature survey, followed by an indication of future challenges.

Overview of band selection process

Figure 1 shows the general framework for the band selection process in hyperspectral image processing. In the process of band selection, a subset of a few suitable bands is selected from the original hyperspectral data, where the physical properties of the original data are preserved. Let the hyperspectral image cube be represented as $\chi \in R^{H \times W \times N}$, where H and W are the height and width of the hyperspectral image cube and N is the total number of spectral bands. Assume that k classes in the hyperspectral data are denoted as $\Omega = [\Omega_1, \ldots\ldots\ldots\ldots, \Omega_k]$.

In the process of hyperspectral band selection, irrelevant and redundant bands are discarded, because they are not relevant or important with respect to the land cover classes of hyperspectral images. When the number of samples is much less than the number of features, processing of the hyperspectral data becomes challenging, because of the Hughes phenomenon. The general process for band selection consists of four key steps as shown in Figure 2: 1) Band subset generation, 2) Evaluation of band subset, 3) Stopping criteria and 4) Validation of results.

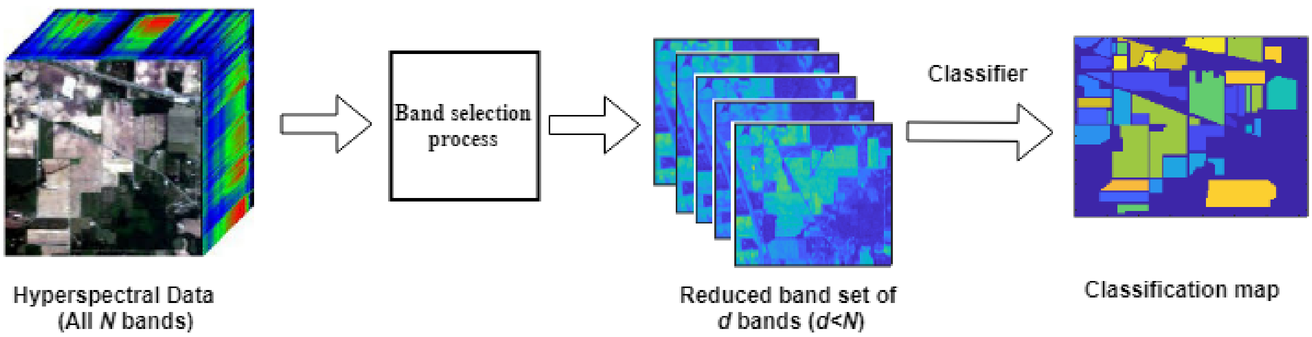

Figure 1. General framework of the band selection process.

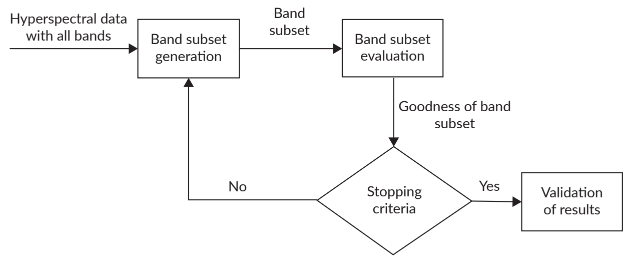

Figure 2. Stages of the band selection process.

Band subset generation specifies a candidate subset for evaluation in the search space. Two simple concerns are considered for determination of the nature of the band subset generation process. First, band subset generation chooses the starting point of the search process, which guides the search direction. To choose the search starting points, scoring, forward, backward and random methods may be considered. Second, the band selection process is carried out with a specific strategy, such as sequential search or exhaustive search. A newly generated band subset is evaluated using certain evaluation criteria. Many evaluation criteria have been proposed in the literature for determination of the goodness of the candidate subset of features. Finally, to stop the selection process, stop criteria must be determined. The band selection process stops at validation, which is not part of the band selection process. However, the band selection method must be validated by carrying out different tests and comparisons with previously established results or by comparison with the results of competing methods.

Band selection approaches

The hierarchical structure of band selection methods based on the basic taxonomy of band selection methods is shown in Figure 3. Band selection methods are subcategorised according to subset evaluation criteria, availability of prior information and selection strategy used to create the band subset. A brief introduction of all subcategories is given in the following sections.

Band selection based on band subset evaluation criteria

Based on subset evaluation criteria, band selection techniques are categorised as the filter method, the wrapper method and the hybrid method. The filter approach selects the bands where the selection criteria are independent of the classifiers used, subsequently, to perform classification of the data. However, the wrapper approach performs band selection based on the classification performance of a given classifier, for example, *k*-nearest neighbour, maximum likelihood, support vector

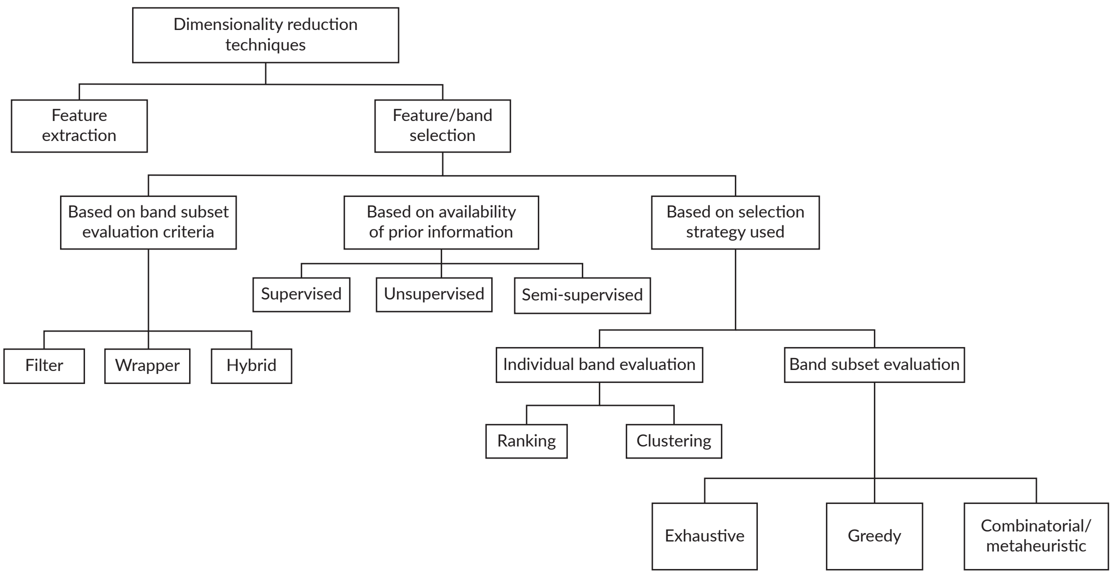

Figure 3. The hierarchical structure of band selection methods based on the basic taxonomy of band selection methods.

machines (SVM) or logistic regression. The hybrid band selection approach is a combination of the filter and wrapper approaches. Filter approaches are usually faster than wrapper approaches as they have lower computational cost. On the other hand, wrapper approaches usually have better performance than filter approaches as they select more representative bands from the original band set.

Goodness of band subset is evaluated using certain evaluation criteria. These criteria are either dependent or independent of the learning algorithm. Generally, the filter approach uses independent evaluation criteria such as information measures (divergence, entropy or mutual information),[21,26–28] distance measures [Bhattacharya distance, Kullback–Leibler divergence, Jeffries–Matusita distance, Hausdorff distance or Spectral Angle Mapper (SAM)][29–32] and dependency measures (correlation measures, similarity measures).[33,34] On the other hand, the wrapper approach uses dependent evaluation criteria.[35–38] Dependent evaluation criteria require a predefined learning algorithm. The performance of the algorithm is used to evaluate the goodness of the band subset, which then determines the optimal subset of bands.

The hyperspectral data consist of discrete spectral bands. To compute the information contained, each band is considered as a discrete random variable B. The mathematical expressions of some of the evaluation criteria used for band selection are given below.

Entropy

According to information theory, the amount of information is measured with Shannon entropy. The Shannon entropy of a discrete random variable B with probability distribution $p(b)$ can be written as:

$$H(B) = -\sum_{b\in B} p(b)\log p(b) \quad (1)$$

Subject to

$$\sum_{b\in B} p(b) = 1$$

$$p(b) = \frac{h(b)}{M\times N} \quad (2)$$

where $h(b)$ is a grey-level histogram of band B and the total number of pixels in band B is given by $M\times N$.

Mutual information

The mutual information between two bands, B_m and B_n, with joint probability distribution $p(b_m,b_n)$ and marginal probability distribution $p(b_m)$ and $p(b_n)$, can be expressed as:

$$I(B_m,B_n) = \sum_{b_m\in B_m, b_n\in B_n} p(b_m,b_n)\log\frac{p(b_m,b_n)}{p(b_m),p(b_n)} \quad (3)$$

$$p(b_m,b_n) = \frac{h(b_m,b_n)}{M\times N} \quad (4)$$

where $h(b_m,b_n)$ is the grey-level histogram of bands B_m,B_n.

Bhattacharya distance

The Bhattacharya distance between bands B_m and B_n is defined as

$$B_{m,n} = \frac{1}{8}(\mu_m-\mu_n)^T\left(\frac{\Sigma_m+\Sigma_n}{2}\right)^{-1}(\mu_m-\mu_n)+\frac{1}{2}\ln\left(\frac{\left|(\Sigma_m+\Sigma_n)/2\right|}{\left|\Sigma_m\right|^{\frac{1}{2}}\left|\Sigma_n\right|^{\frac{1}{2}}}\right) \quad (5)$$

Here, μ_i and μ_j are band means and Σ_i and Σ_j are band covariance matrices.

Kullback–Leibler divergence

The Kullback–Leibler divergence between bands B_m and B_n is expressed as:

$$B_{m,n} = \sum_{b_m\in B_m, b_n\in B_n} p(b_m,b_n)\log\frac{p(b_m)}{p(b_n)} \quad (6)$$

Jeffries–Matusita distance

The Jeffries–Matusita distance between bands B_m and B_n is expressed as:

$$JM_{B_m} = \sqrt{2(1-e^{B_{m,n}})} \quad (7)$$

where $B_{m,n}$ is the Bhattacharya distance calculated using Equation (6).

Hausdorff distance

The Hausdorff distance for band B_m is expressed as:

$$d_{B_m} = \frac{1}{k\times(k-1)}\sum_{i=1}^{k-1}\sum_{j=i+1}^{k}\max\left\{h(cl_i,cl_j),h(cl_j,cl_i)\right\} \quad (8)$$

$$h(cl_i,cl_j) = \max_{x_m\in cl_i}\ \min_{x_l\in cl_j}\left\|x_m-x_l\right\| \quad (9)$$

where x_m is the pixel vector associated with class cl_i and x_l is the pixel vector associated with class cl_j.

Correlation coefficient

The correlation coefficient between bands B_m and B_n is expressed as:

$$CC = \frac{Cov(B_m, B_n)}{\sigma_m \sigma_n} \tag{10}$$

where *Cov* is the covariance between the two bands, σ_m and σ_n are standard deviations of the respective bands.

Overall accuracy

Overall accuracy is a dependent evaluation criterion and is evaluated using a classifier.

$$\text{Overall accuracy} = \frac{\Sigma\, \text{assess}(Y_i)}{m} \tag{11}$$

where m is the total number of pixels in the image and assess(Y_i) is the function used to classify Y_i.

$$\text{assess}(Y_i) = \begin{Bmatrix} 1; \text{if classify}(Y_i) = \Omega \\ 0; \text{otherwise} \end{Bmatrix} \tag{12}$$

Classify (Y_i) is the function that gives the class of Y_i. For the pixel Y_i with true class, the function assess(Y_i) = 1 and 0 otherwise.

Band selection based on availability of prior information

Based on the availability of prior information, the band selection techniques are categorised as supervised band selection,[30,35,39,40] semi-supervised band selection[23,32,41] or unsupervised band selection.[42–45]

Supervised band selection methods need a collection of labelled data, which is a very costly and time-consuming process to generate. Supervised band selection approaches use an evaluation criterion that maximises the class separability of training data samples with known class labels. With limited labelled samples, the supervised band selection method fails to identify the discriminative bands. As the collection of class information *a priori* is an expensive and time-consuming task, the unsupervised band selection methods are more suited to band selection in practice. Though the unsupervised band selection approach performs better in the presence of limited unlabelled data, the lack of discriminative information generally leads to an unsatisfactory classification performance. Hence, the semi-supervised approach is gaining attention for band selection. Such methods use both labelled and easily available unlabelled data samples. By using limited labelled and unlabelled samples, semi-supervised band selection approaches can combine the advantages of both supervised and unsupervised band selection methods. They be categorised into two types: manifold learning based[46] and clustering based.[47,48]

In recent years, spatial information has been taken into account and some spectral–spatial-based band selection methods have been proposed. These methods have provided significant advantages in terms of improving performance.[49–56] For hyperspectral image processing, spatial information means that we take into account the information from neighbouring pixels when making a decision about the current pixel, thereby potentially improving the decision accuracy. In Reference 23, a semi-supervised learning method is proposed for band selection in hyperspectral imagery. With the introduction of hypergraphs for hyperspectral pixel similarity calculation, a better relationship between multiple samples can be captured than using the traditional graph method; hypergraphs are constructed by incorporating both spectral and spatial spaces. An automatic band selection method is proposed for band selection by exploiting spatial structure to determine the discriminating power of each band.[49] An unsupervised band selection algorithm is proposed in Reference 50 based on spatial information. A band selection method in hyperspectral imagery is proposed in Reference 53 that takes into consideration a few selected cluster average values using the spatial information from each band. A multiple spatial feature extraction and fusion method is proposed in Reference 24 to reduce dimensionality. Using the complementary information of different features, the spatial feature extraction method may be a better choice for reducing the dimensionality of hyperspectral images before band selection. In Reference 56, two semi-supervised wrapper-based band selection algorithms are proposed to incorporate spatial information into band selection.

Band selection based on selection strategy used

There are two major approaches to band selection based on selection strategies: individual band evaluation and band subset evaluation. Individual evaluation consists of clustering-based methods[47,57] and ranking-based methods.[58–60] In Individual band evaluation, the score (which signifies the importance of the band) of an individual band is measured according to a certain criterion, such as non-Gaussianity,[22] variance,[61] mutual information[62] etc. In band subset evaluation, candidate band subsets are created by search strategies such as exhaustive search,[63–67] greedy search[68–71] and combinatorial or metaheuristic optimisation methods.[72–76]

Individual evaluation-based band selection

Clustering-based band selection consists of two steps. First, band subsets are formed by grouping the similar bands and separating dissimilar bands within the clustering framework. In the second step, the centroids of the clusters are then considered as the most representative bands and picked out to constitute the final band subset. Clustering is a commonly used method of selecting discriminative bands and the selected discriminative bands are considered as the cluster centres.[77] In Reference 78, sparse subspace clustering is used to select the most suitable band subset. In Reference 57, a dual clustering method is proposed by also employing the background information in the clustering procedure. In Reference 79, based on a hierarchical structure, bands are clustered in order to maximise the inter-cluster variance and minimise the intra-cluster variance. A novel hyperspectral band selection approach is proposed in Reference 80, where a representative band is selected based on maximum weight strategy. However, clustering-based band selection methods focus mainly on redundancy among the bands. Consequently, the most suitable and informative bands may be discarded in the selection process.[34,60,79] In the ranking-based band selection method, bands are selected based on their ranking, in which the rank of each band is first computed according to a definite evaluation criterion (as mentioned above), and then the top-ranked bands are sorted in a sequence to form the subset. The most commonly used ranking methods are maximum variance-based principal component analysis (MVPCA) and information divergence (ID)-based methods. The main disadvantage of the ranking methods is that correlation among bands is ignored while evaluating the discriminating ability of a band. As a result, most of the time, the ranking-based methods select the redundant bands.

To consider both redundancy as well as correlation among the bands, the combination of clustering- and ranking-based methods are discussed.

Subset evaluation-based band selection

Hypothetically, a band selection method by exhaustive search is a direct approach and finds the optimum among all possible subsets according to a certain evaluation criterion. If n bands exist in the original band set, then the optimal band selection procedure requires the evaluation of 2^n band subsets in order to identify the best subset. However, this procedure is not practical as it is too expensive, time-consuming and essentially impossible. To avoid testing all the possible combinations of bands, which imposes a heavy computational burden when selecting the band subset, greedy search strategies, e.g. Sequential Forward Selection (SFS), Sequential Backward Elimination (SBE), Sequential Forward Floating Selection (SFFS) and Sequential Backward Floating Selection (SBFS), can be used. SFS and SBE are fast; however, they do not permit feedback so that earlier selected bands can be reviewed. Therefore, once a band is selected, it will not be removed in a later iteration. SFFS and SBFS provide enhanced strategies of searching by re-evaluating the selected bands for addition or removal at each iteration.

Over the years, in the literature, numerous band selection approaches have been presented based on optimisation inspired by Nature (also called metaheuristic algorithms) including Ant Bee Colony (ABC), Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), Cuckoo Search (CS) optimisation algorithm, Grey Wolf Optimisation (GWO), Differential Evolution (DE) and so on.[29,81–84] These methods consider the band selection problem as a combinatorial optimisation problem, which is solved by formulating an appropriate fitness function or objective function. The objective function evaluates the band subsets and returns the degree of their goodness. The objective function needs to be defined carefully as it influences the performance of the system. It can be dependent or independent of the learning algorithm. Hence, the objective function can be modelled by dependent or independent evaluation criteria as mentioned above. Selection of an effective search strategy is very important in band selection. To optimise the objective function, an appropriate optimisation algorithm must be chosen which converges to the global optimum solution and does not get stuck in a local optimum.

Table 1 details the categorisation of band selection approaches in representative papers published on hyperspectral image classification, including the search or selection strategy used, the techniques used and the performance of the system.

Table 1. Categorisation of band selection approaches in representative papers published on hyperspectral image classification.

Band selection strategy	References	Technique used	Comments on performance of the system
Band subset evaluation based on: Filter			
Band selection based on availability of prior information: Unsupervised			
Ranking	21, 22, 28, 62, 81, 85–105	A score of each band is calculated which is used as a ranking criterion to create a combination of the most discriminative bands. To estimate the relevance of a band, various ranking criteria can be used, such as information theory measures, correlation-based measures and distance-based measures.	Classifier independent. The correlation between bands is not measured during the selection process, which leads to the state where the dependency among the chosen bands is quite high. Highly stable and highly correlated band subsets.
Clustering	34, 53, 57, 77–80, 98, 106–121	Bands are grouped into clusters by means of K-Means, Fuzzy C-Means and hierarchical clustering, in which the inter-cluster variance is maximised and the intra-cluster variance is minimised. In a second step, a representative band is chosen as the best.	Classifier independent. Considers the dependency among the bands, which gives a less correlated band subset. Sensitive to initial cluster centres, repetitive calculations increase the computational burden.
Clustering and ranking	58, 60, 122, 123	Both ranking-based and clustering-based techniques are combined in a single framework. Hence, both information content and redundancy among bands are taken into consideration.	Classifier independent. Less correlated and highly stable band subset.
Clustering + branch and bound search	124	Bands are clustered by a spectral clustering algorithm, then branch and bound search is used to find optimal band subset.	Classifier independent. Sensitive to initial cluster centres.
Combinatorial/ metaheuristic search	26, 42, 54, 72–76, 125–127	Band selection problem as combinatorial optimisation problem, which is solved by formulating an appropriate fitness or objective function. The objective function is formulated by considering the band separability measures.	Classifier independent.
Greedy search	25, 31, 33, 44, 45, 50, 61, 68–71, 128–139	Bands are selected using sequential searching such as SFS, SBE, SFFS, SFBS.	Searching an optimal band subset with a sequential band selection process cannot guarantee an optimal solution. Classifier independent.
Exhaustive search	63–67	Tests all possible combinations of band subsets.	Classifier independent. Excessive computation complexity.

Band selection based on availability of prior information: Supervised			
Greedy search	30, 35, 39, 40	Uses labelled samples. Bands are selected using sequential searching such as SFS, SBE, SFFS, SFBS.	Classifier independent. Fails to identify the most highly discriminative band within the limited labelled samples.
Ranking	23, 140	Uses the unlabelled samples to assist the labelled ones to select highly discriminative and informative features.	Classifier independent. Fails to identify the most highly discriminative band within the limited labelled samples. Highly stable and highly correlated band subsets.
Combinatorial/ metaheuristic search	141	A band subset is produced by using search techniques and a subset evaluation process evaluates the goodness of the corresponding candidate subset by some criterion. Objective function used is classifier accuracy.	Classifier independent. Fails to identify the most highly discriminative band within the limited labelled samples.
Band selection based on availability of prior information: Semi-supervised			
Exhaustive search	32, 46	Uses both unlabelled and labelled samples. Tests all possible combinations of band subsets.	Classifier independent. Excessive computation complexity.
Clustering	47, 48	Bands are clustered by both unlabelled and labelled samples according to similarity measures such as the conditional entropy and conditional mutual information (MI). A representative band from each cluster is selected with value.	Sensitive to initial cluster centres. Classifier independent. Less correlated band subset.
Combinatorial/ metaheuristic search	41	Band selection problem as combinatorial optimisation problem, which is solved by formulating an appropriate fitness or objective function. Objective function is formulated by considering the band separability measures.	Classifier independent.
Band subset evaluation based on: Wrapper			
Band selection based on availability of prior information: Supervised			
Exhaustive search	142, 143	Tests all possible combinations of band subsets. Band selection is achieved through classifier selection.	Classifier dependent. Searches all possible combinations. High computational cost.
Greedy search	70, 144	Bands are selected using sequential searching such as SFS, SBE, SFFS, SFBS.	Classifier dependent. High computational cost.

Combinatorial/ metaheuristic search	36, 38, 83, 145–156	Band selection problem as combinatorial optimisation problem which is solved by formulating an appropriate fitness or objective function. The objective function is formulated by considering the overall accuracy of the classifier.	Classifier dependent. High computational cost.
Band selection based on availability of prior information: Unsupervised			
Greedy search	157	Selects band by integrating overall accuracy and redundancy.	Classifier dependent. High computational cost. Highly stable and highly correlated band subsets.
Band selection based on availability of prior information: Semi-supervised			
Greedy search	56, 158	Uses labelled and unlabelled samples, and sequential search strategy.	Classifier dependent. High computational cost.
Band subset evaluation based on: Hybrid			
Clustering/ combinatorial/ metaheuristic search	29, 159, 160	Combines both filter and wrapper methods.	Sensitive to initial cluster centres. Classifier dependent. High computational cost.

Discussion and conclusion

The selection of suitable and highly discriminative bands is essential for hyperspectral image processing, as hyperspectral images consist of hundreds of highly correlated spectral bands. However, classification performance is restricted by the availability of the number of labelled samples. In this review article, an overview of various band selection approaches has been presented to address the challenges faced by the current system. In this section, this work is summarised by outlining the research challenges faced by the band selection approaches:

1) Most of the band selection approaches select the bands individually, disregarding the relationships among them. Therefore, selected bands fail to represent the characteristics of the original data.
2) Water absorption or noisy bands have low-discriminating capability and need to be manually removed. However, the removal of these low-discriminating bands is a very expensive, time-consuming process and requires expert knowledge.
3) Noisy bands usually result in large spectral divergence. Noisy bands have fewer intra-band correlations and they tend to be easily selected. However, this may not produce a band subset of suitable bands for the clustering-based approach. Also, clustering-based approaches are sensitive to the initial number of clusters, leading to undesirable band subsets.
4) Although a combinatorial optimisation search strategy produces a desirable band subset, it is sensitive to the initialisation strategy and may produce an unreliable band subset.
5) An appropriate band subset searching strategy which ensures the use of an appropriate learning algorithm is required.
6) How to compute the distance between the spectral bands as well as in what way to select the discriminative set of bands are still challenging tasks in hyperspectral band selection.
7) How to decide the minimum number of spectral bands is still challenging issue.
8) Although ranking-based band selection approaches use different evaluation criteria, they generally select individually informative bands. However, the combination of individually informative bands would result in undesirable band subset. This is due to the fact that selected bands have large amounts of redundant information and provide little extra information.

Therefore, in order to address these challenges, there is a need to develop a suitable and automatic band selection strategy which reduces the size of a hyperspectral image without compromising classification accuracy. Such an automatic band selection strategy should decide the minimum number of bands needed to process the hyperspectral data.

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