2. Literature Review

All The literature review of hyperspectral image classification fall under three categories supervised hyperspectal image classification, unsupervised hyperspectal image classification, semisupervised hyperspectal image classification to handle the various issues which are faced while classifying hyperspectral images such as large number of spectral channels, acquisition of labeled data etc. The task of acquisition of labeled data is time consuming and costly. And last part of this section introduces the some well known applications of hypergraph.

2.1 Supervised Classification Methods to Hyperspectral Image Classification

Bands are selected using mutual information (MI). Mutual information term calculate the statistical dependence between two random variable form which it easy to understand relevance of that particular band to classification. Those most relevant bands are selected for further analysis of image which in turns handles the issue of high dimensionality [1].

Supervised Kernel nonparametric weighted feature extraction (KNWFE) method is proposed in [2] to extract the relevant features. This method combines kernel methods and nonparametric weighted feature extraction method to possess both linear and nonlinear transformation.

In [4] supervised method based on a stochastic minimum spanning forest (MSF) approach to classify hyperspectral data is proposed. In this method a pixel wise classification is first performed on hyperspectal image .From this classification map, marker maps are created with random selection of pixels and labeling them as markers for the purpose building of MSFs. MSF is built from each of the marker maps and final classification map generated with a maximum vote decision rule.

As these methods fall under supervised category they make use of only labeled data to train the classifier and in case of hyperspectral images label data is a very few and obtaining labeled data is more time consuming and costly. So research goes towards such methods which will conduct hyperspectral image classification under a very few training samples or absence of samples

2.2 Unsupervised Classification Methods to Hyperspectral Image Classification

In [5] unsupervised method based on fuzzy approach which uses linear 1-D discrete wavelet transform (DWT) for reducing dimensionality of hyperspectral data. In this approach segmentation of hyperspectral images by applying fuzzy c-means (FCM) clustering as well as its extended version Gustafson–Kessel clustering (GKC). Image categorization is done with the help of hypergraph partition [6]. Hypergraph has advantages over simple graph. Complex relationship between unlabeled is represented with help of hypergraph.

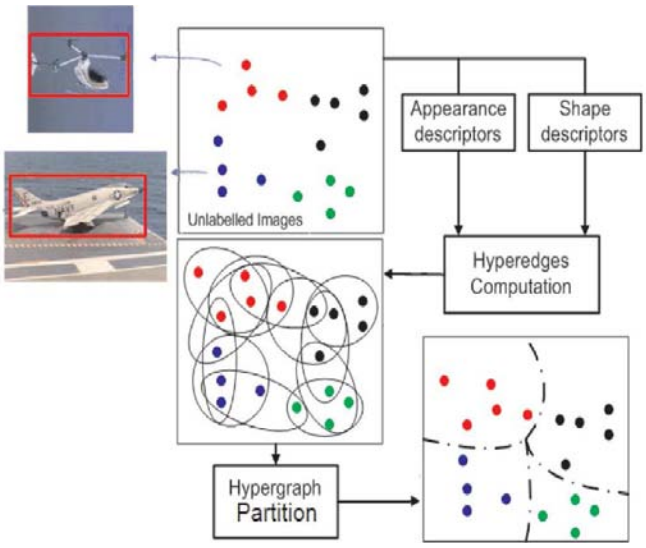


Figure 1: Image categorization by hypergraph partition [6]

In this procedure unsupervised method is conducted to select the Region of Interests (ROIs) of the unlabeled images. Based on the appearance and shape descriptors extracted from the ROIs to measure two types of similarities between images from which two kinds of hyper edges are formed and compute their corresponding weights based on these two kinds of similarities, respectively. In this way relationships among three or more images described, besides the merits of shape and appearance characteristics are incorporated naturally to boost the clustering performance.

As discussed above all the unsupervised methods are insensitive to the number of labeled data since these methods work on the whole image, but the relationship between clusters and classes is not guaranteed. The use of semi-supervised classifiers e in these situations can help to improve the classification accuracy.

2.3 Semisupervised Classification Methods to Hyperspectral Image Classification

In semi-supervised methods the algorithm is provided with some available labeled data in addition with unlabeled data. In literature three different classes of semi-supervised learning algorithm s are introduced

1. Generative models-In these types of algorithm conditional density p(x|y) (e.g. expectation maximization (EM) algorithms with finite mixture models are calculated.
2. Low density separation –These algorithms, maximize the hyperplane between labeled and unlabeled samples simultaneously (e.g. Transductive SVM [7]).
3. Graph-based methods-Each sample spreads its label information to its neighbors until a global stable state is achieved on the whole data set.

Semisupervised version of neural network introduced to overcome limitations of TSVM such as falling under local minima by adding a regularizer to the loss function which issued for training neural networks [8].

Semisupervised version of conditional random field (CRF) graph structure and higher order potentials, which can model complex relationship of hyperspectral images, along with piecewise training model to train the sample data is introduced in [9].

R. Ji et al. proposed spectral-spatial constraint hyperspectral image classification method. In this method spatial context is introduced to handle issues such as large numbers of spectral channels and lack of labels. Hypergraph is constructed using two hyperedges feature based and spatial based hyperedge. To get final classification result semisupervised learning is carried over constructed hypergrah [10].

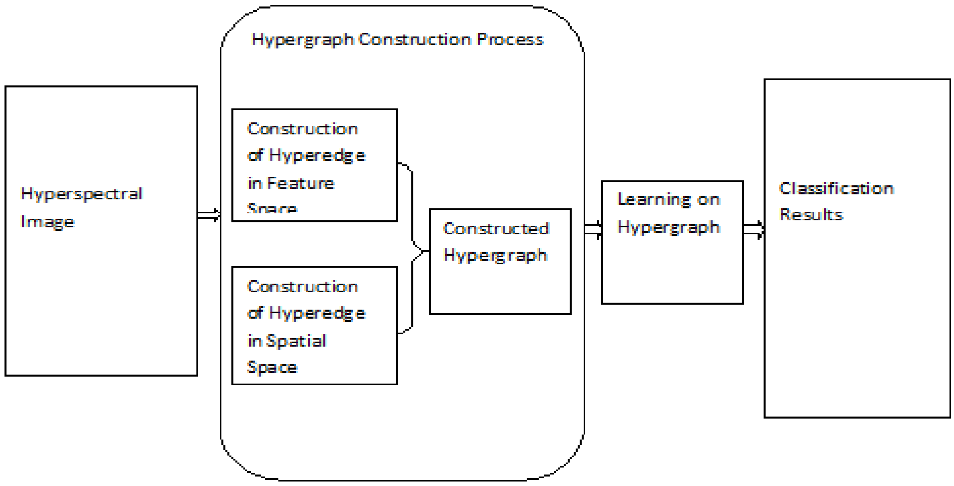


Figure 2: Flowchart for spectral-spatial constraint hyperspectral image classification method

- Construction of hyperegde in feature space:

To construct hyperedge in feature space the pixels which are close to each other in feature space are connected to form hyperedge .This closeness is measured in distance metric. The pixels with small distance are considered as close to each other. The pixels which are close to each other has same label. The process of constructing feature based hyperedge is shown in following figure.

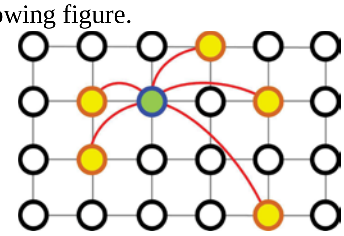
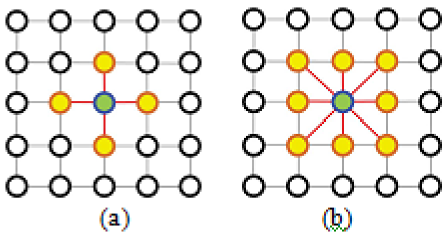


Figure 3: Construction of hyperedge in feature space [10]

In fig 3 the blue-green pixel is the centroid, and its five yellow colored pixels are neighbors. From these selected pixels hyperedge is constructed by connecting six pixels.

- Construction of hyperedge in spatial space: The hyperedge in spatial space is constructed by each pixel making each pixel as centroid and its spatial neighbors.Fig 4 shows the four types spatial based hyperedge.



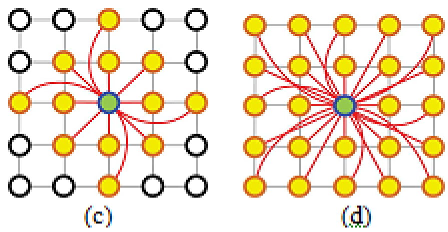


Figure 3: Construction of hyperedge in spatial space [10]

The blue green pixel is the centroid, and it connects yellow pixels its spatial-based. Four types of hyperedes are constructed having 4, 8, 12, 24 spatial neighbors. In this way, both the feature and the spatial information of hyperspectral image can be concurrently considered and semisupervised learning method is conducted over constructed hypergraph to get precise hyperspectral image classification.

The improvement in this method required as system neglect the some pixels for the purpose of reduction in computational burden. Yue Gao et al. [11] proposed the improved version of hypergraph construction performed in two steps. At first simple graph constructed and unsupervised learning conducted over simple graph to identify grouping relation while in second step hypergraph constructed from previous step and semisupervised learning conducted to achieve desired classification result.

2.4 Applications of hypergraph

Hypergraph constructed to represent the complex relationship in various applications. This large extent use of hypergraph has shown the importance in hyperspectral image classification. This section introduced some well known application where hypergraph provides better way to model the relationship.

A transductive learning framework for image retrieval in which images are taken as vertices in a weighted hypergraph and the image search task is formulated as the problem of hypergraph ranking in [12]. Based on the similarity matrix computed from various feature descriptors, each image represented as a 'centroid' vertex and a hyperedge is formed by a centroid and its k-nearest neighbors. Probabilistic hypergraph is also proposed, which presents not only whether a vertex v_i belongs to a hyperedge e_j , but also the probability that $v_i \in e_j$. In this way, both the higher order grouping information and the local relationship between vertices within each hyperedge are described. In this way, the task of content based image retrieval with relevance feedback is converted to a transductive learning problem which can be solved by the hypergraph ranking algorithm.

In [13], to estimate relevance user tagged images tags and visual characteristics are simultaneously exploited. The learning is conducted through constructing hypergraph of social images. In this hypergraph vertices represent images and hyperedges represent visual or textual terms. a relevance learning procedure is performed on the hypergraph structure where a set of pseudo-relevant samples are employed. Learning not only estimate the relevance scores among images but also the weights of hyperedges. By using the learning of hyperedge weights, the effects of uninformative tags and visual words can be minimized.

Two challenges confronts during music recommendation :(a) There are many different types of objects and relations in music social communities, which makes it difficult to develop a unified framework taking into account all objects and relations. (b) In these communities, some relations other than pairwise relation. hypergraph is constructed to model the various objects and relations, and music recommendation considered as a ranking problem on this hypergraph in [14].

In [15], 3-D Object Retrieval and Recognition can be achieved through hypergraph construction and analyzing the that hypergraph. Multiple hypergraphs for a set of 3-D objects based on their 2-D views are constructed. In these hypergraphs, each vertex is an object, and each edge is a cluster of views. Therefore, an edge connects multiple vertices. It explores the higher order relationship among 3-D objects. Here, the higher order relationship of objects is encoded in the hypergraph structure, i.e., the connection of each edge to multiple vertices.

3. Conclusion

Remote sensing is becoming promising research field in current days. Hyperspectral classification become promising task because of some challenging task like Curse of dimensionality, Few labeled samples, the spatial variability of the spectral signature, exploring Spatial correlation among pixels and adding contextual information along with spectral information during classification. This letter gives some well known techniques based on how training samples are used to classify the hyperspectral data. Future research will be in direction of constructing hypergraph and conducting learning on hypergraph to get final classification results.

References

[1] M. Fauvel, Y. Tarabalka, J. A. Benediktsson, J. Chanussot, and J. C. Tilton, "Advances in Spectral-Spatial Classification of Hyperspectral Images," Proc. IEEE, Mar. 2013 ,vol. 101, no. 3, pp. 652–675.
[2] B. Guo, S. R. Gunn, R. I. Damper, and J. D. B. Nelson,"Band Selection for Hyperspectral Image Classification using Mutual Information ," IEEE Geosci. Remote Sens.Lett. vol. 3, no.4, pp. 522–526, Oct. 2006.
[3] B.-C. Kuo, C.-H. Li, and J.-M. Yang, "Kernel Nonparametric Weighted Feature Extraction for Hyperspectral Image," IEEE Trans. Geosci. Remote Sens. vol. 47, no. 4, pp. 1139–1155, Apr. 2009.
[4] K. Bernard, Y. Tarabalka, J. Angulo, J. Chanussot, and J. A. Benediktsson, "Spectral-Spatial Classification of Hyperspectral Data Based on a Stochastic Minimum Spanning Forest Approach," IEEE Trans. Image Process, vol. 21, no. 4, pp. 2008–2021, Apr. 2012.
[5] G. Bilgin, S. Erturk, and T. Yildirim, "Unsupervised Classification of Hyperspectral-Image Data using Fuzzy Approaches that Spatially Exploit Membership Relations," IEEE Geosci. Remote Sens. Lett., vol. 5, no. 4, pp. 673–677, Oct. 2008
[6] Y. Huang, Q. Liu, F. Lv, Y. Gong, and D. Metaxas, "Unsupervised Image Categorization by Hypergraph Partition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 6, pp. 1266–1273, Jun. 2011.
[7] L. Bruzzone, M. Chi, and M. Marconcini, "A Novel Transductive SVM for Semisupervised Classification of Remote Sensing Images," IEEE Trans. Geosci. Remote Sens., vol. 44, no. 11, pp. 3363–3373, Nov.2006.
[8] F. Ratle, G. Camps-Valls, and J. Weston, "Semi-Supervised Neural Networks for Efficient Hyperspectral Image Classification," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 5, pp. 2271–2282, May 2010.
[9] P. Zhong and R. Wang, "Modeling and Classifying Hyperspectral Imagery by CRFs With Sparse Higher Order Potentials," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 2, pp. 688–705, Feb. 2011.
[10] R. Ji, Y. Gao, R. Hong, Q. Liu, D. Tao, and X. Li, "Spectral-Spatial Constraint Hyperspectral Image Classification," IEEE Trans. Geosci. Remote Sens., vol. 52, no. 3, pp. 1811–1824, Mar. 2014.
[11] Yue Gao, Rongrong Ji, Peng Cui, Qionghai Dai, and Gang Hua, "Hyperspectral Image Classification through Bilayer Graph-Based Learning", IEEE Trans on Image Processing, vol. 23, no. 7, July 2014.
[12] Y. Huang, Q. Liu, S. Zhang, and D. Metaxas, "Image Retrieval via Probabilistic Hypergraph Ranking," in Proc. IEEE Conf. CVPR, Jun. 2010, pp. 3376–3383.
[13] Y. Gao, M. Wang, Z. Zha, J. Shen, X. Li, and X. Wu, "Visual-Textual Joint Relevance Learning for Tag-Based Social Image Search," IEEE Trans. Image Process., vol. 22, no. 1, pp. 363–376, Jan. 2013.
[14] J. Bu et al., "Music Recommendation by Unified Hypergraph: Combining Social Media Information and Music Content," in Proc. ACM Int. Conf. Multimedia, 2010, pp. 391–400.
[15] Y. Gao, M. Wang, D. Tao, R. Ji, and Q. Dai, "3D Object Retrieval and Recognition with Hypergraph Analysis," IEEE Trans. Image Process., vol. 21, no. 9, pp. 4290–4303, Sep. 2012.

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