International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No. (03), January 2018
www.ijarse.com
IJARSE
ISSN: 2319-8354

A Survey on Classification of Remote Sensing Data using Machine Learning Algorithms

M.Praneesh[1], D.Napoleon[2]

[1]*Research Scholar;Department of Computer Science*
Bharathiar University
[2]*Assistant Professor,Department of Computer Science*
Bharathiar University

ABSTRACT

Due to elevated number of spectral channels and large information of size, classification of Remote sensing data are difficult to be processed and classified with high accuracy and less computational time. In general, large quantity of data collected from the GIS namely satellite, aerial sensors, and telescope. Numerous classification techniques have been designed for the analysis of Remote sensing data. In this context, analyzing the best classification algorithm is big issue in Image processing field. In this literature survey, summarize the advanced techniques which are based on Clustering and SVM. Moreover we have provided the guidelines to future researchers to enhance further algorithmic developments in Remote sensing applications.

Keywords: Remote sensing Data, Clustering, SVM.

I.INTRODUCTION

Remote sensing is the techniques which provide the modern information about an area such as Land cover classification, climate, minerals, vegetation, marine resources, urban monitoring, forestry, disaster management, robot navigation and many others with the help of sensors but without having any direct contact with the objects. When we classifying the remote sensing data, the necessary algorithm were implemented to carry out the interpretation and analysis of Electromagnetic spectrum. The major steps of image classification involve image preprocessing, detection and extraction of object, feature extraction, selection of training samples, algorithms and accuracy assessment. For remotely sensed scene analysis, images of the earth's surface arc captured by sensors in remote sensing satellites or by a multi-Spectra) scanner housed in an aircraft and then transmitted to the Earth Station for further processing [3, 4]. In this paper we have summarized some of the traditional algorithms which are based on SVM and Clustering. Clustering is the process of organizing the objects into groups. Support vector machine is a nonparametric statistical method for addressing supervised classifications and regression problems. In SVM, kernel functions that accurately reflect the similarity among the samples and also satisfy the Mercer's condition are linear kernel, polynomial kernel, radial basis function kernel and sigmoid kernel. The rest of the paper organized as follows. Section 2 describes the overview and analysis of Clustering, section 3 deals with the classification model based on SVM. Section 4 illustrates the performance measures of Remote sensing data finally section 5 concludes the article.

II.CLUSTERING

Clustering is the process of organizing the objects into groups. In generally is classification methodology is carried out of some the characteristics such as Data collection, Initial screening, representation, clustering tendency, cluster strategy, validation and interpretation. Based on above characteristics classification is carried out two aspects such as supervised classification and unsupervised classification. Clustering has become a widely studied problem in a variety of application domains, such as in data mining and knowledge discovery [1], [2] statistical data analysis [3], [4] data classification and compression [6], medical image processing [5] and bioinformatics [6]. Several algorithms have been proposed in the literature for clustering [7], [8]. A. L. Abul is explained about Cluster Validity Analysis Using Sub sampling [10]. The objective of all clustering algorithms is to divide a set of data points into subsets so that the objects within a subset are similar to each other and objects that are in different subsets have diverse qualities [11], [12], [13]. Bradley and Fayyad have proposed an algorithm for refining the initial cluster centers. Not only are the true clusters found more often, but the clustering algorithm also iterates fewer times. Some clustering 176 methods improve performance by reducing the distance calculations. For example, Judd et al. proposed a parallel clustering algorithm P-CLUSTER which uses three pruning techniques. Ming-Chuan Hung, explained about an Efficient k-Means Clustering Algorithm Using Simple Partitioning based on Remote sensing data. The Table1 describes the analysis of clustering Algorithms.

Table 1 : Clustering Algorithms

Algorithms	RS Data	References
K-Means Clustering	Multispectral, Hyper spectral	[2]
Fuzzy C-Means	Multispectral, Hyper spectral	[4]
Fast and Exact K-means	Multispectral, Hyper spectral	[8]
K-Means based mixture model	Multispectral, Hyper spectral	[5]
Boosting	Multispectral,	[34]

Clustering	Hyper spectral	
Affinity propagation	Multispectral, Hyper spectral	[15]
StrAP	Multispectral, Hyper spectral	[18]
Median Fuzzy C-Means	Multispectral, Hyper spectral	[33]
Fuuzy AP	Multispectral, Hyper spectral	[40]
ED Algorithm	Multispectral, Hyper spectral	[31]
MD Algorithm	Multispectral, Hyper spectral	[56]
CD Algorithm	Multispectral, Hyper spectral	[21]
Fuzzy possiblistic	Multispectral, Hyper spectral	[4]
Modify Fuzzy possiblistic	Multispectral, Hyper spectral	[56]
Kernel Fuzzy possiblistic	Multispectral, Hyper spectral	[25]
Modify kernel fuzzy possiblistic	Multispectral, Hyper spectral	[23]

IV.SUPPORT VECTOR MACHINE

SVMs are nonparametric statistical approaches for addressing supervised classification and regression problems. In this context, SVM determine a hyper plane that discriminates data set into set of classes for classifying the remote sensing data. The SVM approach has been applied first to the classification of hyper spectral data without reducing the dimensionality. In this survey, we have focus on SVM-based approaches, including active SVMs, S^3Vs, and composite SVMs methods for addressing the remote sensing problem. In this article we have analyzed the following machine learning methods.

a. Active Machine Learning

International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No. (03), January 2018
www.ijarse.com
IJARSE
ISSN: 2319-8354

b. Semi supervised SVMs

c. SVMs integrated with other approaches

The table 2 describes machine learning methods based Algorithm for classifying different kinds of RS Data.

Algorithms	RS Data	References
Active SVM	Multispectral	[55]
Adaptive kernel	Hyperspectral	[56]
Bootstrapped SVM	Multispectral	[57]
Batch mode active SVM	MODIS	[60]
TSVM	Hyperspectral	[75]
RVM	Hyperspectral	[78]
P-SVM	Hyperspectral	[80]
Primal SVM	Multispectral	[67]
LapSVM	Hyperspectral	[87]
S^3VM	Multispectral	[99]
Cluster based SVM	Hyperspectral	[100]
GA and SVM	Hyperspectral	[95]
FCM and SVM	Multispectral	[90]
PSO and SVM	Hyperspectral	[98]
Fuzzy clustering and SVM	Hyperspectral & multispectral images	[90]

V.PERFORMANCE MEASURES

A. MEAN SQUARE ERROR

MSE measures the average of the square “error" between the five remote sensing images. The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or

International Journal of Advance Research in Science and Engineering
Volume No.07, Special Issue No. (03), January 2018
www.ijarse.com
IJARSE
ISSN: 2319-8354

because the estimator doesn't account for information that could produce a more accurate estimate. The formula for mean square is given as

$$\text{MSE} = \left[\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left[\hat{f}(i,j) - f(i,j)\right]^2\right]^{1/2}$$

Where M*N is the size of the image, $\hat{f}$(i, j) and f (i, j) are the matrix element of the fused and the original image at (i, j) pixel. To compare the performance, an objective image quality assessment, Mean Square Error (MSE) results of remote sensing images are shown in Table.

B. PEAK SIGNAL TO NOISE RATIO (PSNR)

PSNR for remote sensing images are calculated by using fusion Techniques.

$$\text{PSNR} = 10\log_{10}\left[\frac{MxN}{RMSE}\right]$$

Here remote sensing is original image and noise in error is fused image. In general, a good fused image is one with low MSE and high PSNR **[26]**. That means that the image has low error. To compare the performance, an objective image quality assessment, Peak Signal-to-Noise Ratio (PSNR) results of five remote sensing images are shown in Table.

C. NORMALIZED CROSS CORRELATION

NCC in which the brightness of the image and template can vary due to tighting and exposure conditions, the images can be first normalized. This is typically done at every step by subtracting the mean and dividing by the standard deviation. That is the cross correlation of the template, t(x, y) with sub image f(x, y) is

$$NCC = \frac{1}{n}\sum_{x,y}\frac{\left(f(x,y) - \bar{f}\right)\left(t(x,y) - \bar{t}\right)}{\sigma_f \sigma_t}$$

Where n is the number of pixels in t(x, y) and f(x, y), $\bar{f}$ is the average of f and σ_f is standard deviation of f. In functional analysis terms, can be thoughts of as the dot product of two normalized vectors, that is if F (x, y) = t (x, y) – $\bar{f}$ and T (x, y) = t (x, y) - $\bar{t}$ Then the above sum is equal to F and T is real matrices of Normalized Cross Correlation.

D. AVERAGE DIFFERENCE

The average number of a set is the total of those numbers divided by the number of items in that set and the average brightness of a region is defined as the sample mean of the pixel brightness within that region. The difference in visual properties that makes an object distinguishable from other objects. The formula for average difference is given as

$$AD = \sum_{j=1}^{M} \sum_{k=1}^{N} (x_{j,k} - x'_{j,k}) / \; M\,N$$

E. MAXIMUM DIFFERENCE

As expected the metrics that are responsive to distortions are also almost always responsive to the image set. Conversely, the metrics that do not respond to variation of the image set are also not very discriminating with respect to distortion types. The fact that the metrics are sensitive, as would be expected, to both the image content and distortion artifacts does not eclipse their potential as quality metrics.

F. NORMALIZED ABSOLUTE ERROR

Normalization is the process of isolating statistical error in repeated measured data. Absolute error is the uncertainty in a measurement, which is expressed using the relevant units. Also, absolute error may be used to express the inaccuracy in a measurement. Normalized absolute error formula is given as.

$$NAE = \frac{\sum_{j=1}^{M} \sum_{k=1}^{N} | \, x_{j,k} - x'_{j,k} |}{\sum_{j=1}^{M} \sum_{k=1}^{N} | \, x_{j,k} \, |}$$

G. KAPPA ANALYSIS

Kappa coefficients are widely used as classification accuracy assessment for remote sensed data, the result of performing Kappa Analysis is a KHAT statistic (an estimate of Kappa), which are computed as

$$\hat{K} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} . x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} . x_{+i})}$$

Where r is the number of rows in the error matrix (also called the confusion matrix), x_{ii} is the number of observations in row i and column i, x_{i+} and x_{+i} are the marginal totals of row i and column i, respectively, and N is the total number of observations.

VI.CONCLUSION

In this review article, we have provided a quick reference of the compendium of recently developed SVM-based techniques in RS applications. We also pointed out traditional methods used for image classification. Most of the findings indicate that there is sufficient empirical evidence to support the adoption of these processing algorithms.

IJARSE
ISSN: 2319-8354

REFERENCES

[1] C. Persello, "Advanced techniques for the classification of very high resolution and hyperspectral images," Ph.D. dissertation, International Doctorate School in Information and Communication Technologies, Univ. Trento, Italy, 2010.

[2] D. Lu and Q. Weng, "Survey of image classification methods and techniques for improving classification performance," *Int. J. Remote Sensing*, vol. 28, no. 5, pp. 823–870, Mar. 2007.

[3] U. Maulik and S. Bandyopadhyay, "Fuzzy partitioning using a real-coded variable-length genetic algorithm for pixel classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 5, pp. 1075– 1081, June 2003.

[4] U. Maulik and S. Bandyopadhyay, "Performance evaluation ofsome clustering algorithms and validity indices," *IEEE Trans.Pattern Anal. Mach. Intell.*, vol. 24, no. 12, pp. 1650–1654, Dec.2002.

[5] A. Mukhopadhyay, S. Bandyopadhyay, and U. Maulik, "Clustering using multi-objective genetic algorithm and its application to image segmentation," in *Proc. IEEE Int. Conf. Syst., Man, Cybernetics*, vol. 3, Nov. 2006, pp. 2678–2683.

[6] S. Bandyopadhyay, U. Maulik, and A. Mukhopadhyay, "Multiobjective genetic clustering for pixel classification in remote sensing imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 4, pp. 1132–1138, May 2009.

[7] A. Mukhopadhyay, S. Bandyopadhyay, and U. Maulik, "Combining multiobjective fuzzy clustering and probabilistic ANN classifier for unsupervised pattern classification: Application to satellite image segmentation," in *Proc. IEEE World Congr. Evolutionary Computation*, June 2008, pp. 877–883.

[8] A. Mukhopadhyay, U. Maulik, and S. Bandyopadhyay, "A survey of multiobjective evolutionary clustering," *ACM Computing Surveys*, vol. 47, no. 4, pp. 61:1–61:46, July 2015.

[9] E. Alpaydin, *Introduction to Machine Learning*, 2nd ed. Cambridge, MA: MIT Press, 2010.

[10] J. T. Tou and R. C. Gonzalez, *Pattern Recognition Principles*. Reading, PA: Addison-Wesley, 1974.

[11] P. A. Devvijver and J. Kittler, *Pattern Recognition: A Statistical Approach*. London: Prentice Hall, 1982.

[12] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms*. New York: Plenum, 1981.

[13] R. O. Duda and P. E. Hart, *Pattern Classification and Scene Analysis*. New York: Wiley, 1973.

[14] K. Fukunaga, *Introduction to Statistical Pattern Recognition*. New York: Academic Press, 1990.

[15] T. M. Mitchel, *Machine Learning*. New York: McGraw Hill, 1997.

[16] J. R. Quinlan, "Induction and decision trees," *J. Mach. Learning*, vol. 1, no. 1, pp. 81–106, 1986.

[17] V. Vapnik, *Statistical Learning Theory*. New York: Wiley, 1998.

[18] O. Chapelle, B. Scholkopf, and A. Zien, *Semi-Supervised Learning*, 1st ed. Cambridge, MA: MIT Press, 2006.

[19] X. Zhu. (2005). Semi-supervised learning literature survey. Comput. Sci., Univ. Wisconsin-Madison, WI, Tech. Rep. 1530. [Online]. Available: http://www.cs.wisc.edu/jerryzhu/pub/ssl survey.pdf

[20] M. Hajighorbani, S. M. Reza Hashemi, A. Broumandnia, and M. Faridpour, "A review of some semi-supervised learning methods," *J. Knowl.-Based Eng. Innov.*, vol. 2, no. 4, pp. 250—259, 2016.

[21] A. Blum and T. Mitchell, *Combining Labeled and Unlabeled Data with Co-Training*. San Mateo, CA: Morgan Kaufmann, pp. 92–100, 1998.

[22] N. M. Dempster, A. P. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *J. Roy. Statistical Soc., Series B,* vol. 39, no. 1, pp. 1–38, 1977.

[23] Q. Jackson and D. A. Landgrebe, "An adaptive classifier design for high dimensional data analysis with a limited training set," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 2, pp. 2664–2679, Dec. 2001.

[24] V. Vapnik, *The Nature of Statistical Learning Theory*, 2nd ed. Berlin, Germany: Springer-Verlag, 1999.

[25] K. P. Bennett and A. Demiriz, "Semi-supervised support vectormachines," in *Proc. Advances Neural Information Processing Systems vol. 10*. Cambridge, MA: MIT Press, 1998, pp. 368–374.

[26] S. Dhar and V. Cherkassky, "Development and evaluation of cost-sensitive universum-SVM," *IEEE Trans. Cybern.*, vol. 45, no. 4, pp. 806–818, Apr. 2015.

[27] G. Camps-Valls, T. Bandos, and D. Zhou, "Semi-supervised graph-based hyperspectral image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 10, pp. 3044–3054, Sept. 2007.

[28] U. Brefeld, T. Gartner, T. Scheffer, and S. Wrobel, "Efficient coregularised least squares regression," in *Proc. 23rd Int. Conf. Machine Learning*, Pittsburgh, PA, 2006, pp. 137–144.

[29] M. Li and I. K. Sethi, "Confidence-based active learning," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 8, pp. 1251–1261, Aug. 2006.

[30] V. Vapnik, *The Nature of Statistical Learning Theory*. New York: Springer-Verlag, 1995.

[31] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Knowledge Discovery and Data Mining*, vol. 2,pp. 121–167, June 1998.

[32] V. Vapnik, *Estimation of Dependencies Based on Empirical Data* (in Russian). New York: Springer Verlag, 1982, pp. 5165–5184.

[33] G. Zhu and D. G. Blumberg, "Classification using ASTER data and SVM algorithms; the case study of Beer Sheva, Israel," *Remote Sensing Environment*, vol. 80, no. 2, pp. 233–240, May 2002.

[34] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learning*, vol. 20, pp. 273–297, Sept. 1995.

[35] B. Scholkopf, C. J. C. Burges, and A. J. Smola, *Advances in Kernel Methods: Support Vector Learning*. Cambridge, MA: MIT Press, 1999.

[36] J. R. G. Townshend, "Land cover," *Int. J. Remote Sensing*, vol. 13, pp. 1319–1328, Apr. 1992.

[37] F. G. Hall, J. R. G. Townshend, and E. T. Engman, "Status of remote sensing algorithms for estimation of land surface state parameters," *Remote Sensing Environment*, vol. 51, no. 1, pp. 138–156, Jan. 1995.

[38] R. P. Lippman, "An introduction to computing with neural nets," *IEEE ASSP Mag.*, vol. 4, pp. 2–22, Apr. 1987.

[39] J. D. Paola and R. A. Schowengerdt, "A review and analysis of backpropagation neural networks for classification of remotely sensed multi-spectral imagery," *Int. J. Remote Sensing*, vol. 16, no. 16, pp. 3033–3058, 1995.

[40] P. M. Atkinson and A. R. L. Tatnall, "Neural networks in remote sensing," *Int. J. Remote Sensing*, vol. 18, pp. 699–709, Feb. 1997.

[41] S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Trans. Syst., Man, Cybern.*, vol. 21, pp. 660–674, May 1991.

[42] R. S. DeFries, M. Hansen, J. R. G. Townshend, and R. Sohlberg, "Global land cover classifications at 8 km spatial resolution: The use of training data derived from Landsat imagery in decision tree classifiers," *Int. J. Remote Sensing*, vol. 19, pp. 3141–3168, Nov. 1998.

[43] M. C. Hansen, R. S. DeFries, J. R. G. Townshend, and R. Sohlberg, "Global land cover classification at 1 km spatial resolution using a classification tree approach," *Int. J. Remote Sensing*, vol. 21, no. 6/7, pp. 1331–1364, Apr. 2000.

[44] L. Bruzzone, D. F. Prieto, and S. B. Serpico, "A neural-statistical approach to multitemporal and multisource remote-sensing image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1350–1359, May 1999.

[45] J. A. Benediktsson and I. Kanellopoulos, "Classification of multisource and hyperspectral data based on decision fusion," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1367–1377, May 1999.

[46] L. O. Jimenez, A. Morales-Morell, and A. Creus, "Classification of hyperdimensional data based on feature and decision fusion approaches using projection pursuit, majority voting and neural networks," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 3, pp. 1360–1366, May 1999.

[47] C. Huang, L. S. Davis, and J. R. G. Townshend, "An assessment of support vector machines for land cover classification," *Int. J. Remote Sensing*, vol. 23, no. 4, pp. 725–749, 2002.

[48] G. Mountrakis, J. Im, and C. Ogole, "Support vector machines in remote sensing: A review," *ISPRS J. Photogrammetry Remote Sensing*, vol. 66, no. 3, pp. 247–259, May 2011.

[49] J. A. Gualtieri and R. F. Cromp, "Support vector machines for hyperspectral remote sensing classification," in *Proc. Soc. of Photo- Optical Instrumentation Engineers 27th Appl. Imagery Pattern Recognition Workshop*, vol. 3584, 1998, pp. 221–232 .

[50] G. F. Hughes, "On the mean accuracy of statistical pattern recognition," *IEEE Trans. Inform. Theory*, vol. IT-14, no. 1, pp. 55–63, Jan. 1968.

[51] C. Persello and L. Bruzzone, "Active and semisupervised learning for the classification of remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 11, pp. 6937–6956, Oct. 2014.

[52] L. Bruzzone and B. Demir, "A review of modern approaches to classification of remote sensing data," in *Land Use and Land Cover Mapping Europe, Practices and Trends*, I. Manakos, M. Braun, Eds. New York: Springer-Verlag, Chapter 9, 2014, pp. 127–143.

[53] E. Izquierdo-Verdiguier, L. Gomez-Chova, and G. Camps-Valls, *Kernels for Remote Sensing Image Classification*. Hoboken, NJ: Wiley, 2015.

[54] D. Tuia, M. Volpi, L. Copa, M. Kanevski, and J. Munoz-Mari, "A survey of active learning algorithms for supervised remote sensing image classification," *IEEE J. Sel. Topics Signal Process*, vol. 5,no. 3, pp. 606–617, July 2011.

[55] P. Mitra, B. U. Sankar, and S. K. Pal, "Segmentation of multispectral remote sensing images using active support vector machines," *Pattern Recognition Letters*, vol. 25, no. 9, pp. 1067– 1074, July 2004.

[56] Y. Zhang, X. Liao, and L. Carin, "Detection of buried targets via active selection of labeled data: Application to sensing subsurface UXO," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 11, pp. 2535–2543, Dec. 2004.

[57] M. Ferecatu and N. Boujemaa, "Interactive remote-sensing image retrieval using active relevance feedback," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 4, pp. 818–826, Apr. 2007.

[58] G. Schohn and D. Cohn, "Less is more: Active learning with support vectors machines," in *Proc. 17th Int. Conf. Mach. Learning*, Stanford, CA, 2000, pp. 839–846.

[59] D. Tuia, F. Ratle, F. Pacifici, A. Pozdnoukhov, M. Kanevski, F. Del Frate, D. Solimini, and W. J. Emery, "Active learning of very-high resolution optical imagery with SVM: Entropy versus margin sampling," in *Proc. IEEE Int. Geo. Remote Sens. Symp.*, Boston, MA, July 2008, pp. IV-73–IV-76.

[60] C. Castillo, I. Chollett, and E. Klein, "Enhanced duckweed detection using bootstrapped SVM classification on medium resolution RGB MODIS imagery," *Int. J. Remote Sensing*, vol. 29, no. 19, pp. 5595–5604, Sept. 2008.

[61] D. Tuia, F. Ratle, F. Pacifici, M. F. Kanevski, and W. J. Emery, "Active learning methods for remote sensing image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 7, pp. 2218–2232, July 2009.

[62] N. Abe and H. Mamitsuka, "Query learning strategies using boosting and bagging," in *Proc. 15th Int. Conf. Mach. Learning*, Madison, WI, 1998, pp. 1–9.

[63] B. Demir, C. Persello, and L. Bruzzone, "Batch-mode active learning methods for the interactive classification of remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 3, pp. 1014–1031, Mar. 2011.

[64] S. Patra and L. Bruzzone, "A cluster-assumption based batch mode active learning," *Pattern Recognition Lett.*, vol. 33, no. 9, pp. 1042–1048, June 2012.

[65] C. Persello, "Interactive domain adaptation for the classification of remote sensing images using active learning," *IEEE Geosci. Remote Sens. Lett.*, vol. 10, no. 4, pp. 736–740, June 2013.

[66] G. Jun and J. Ghosh, "An efficient active learning algorithm with knowledge transfer for hyperspectral data analysis," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, vol. 1, July 2008,pp. I-52–I-55.

[67] C. Persello and L. Bruzzone, "Active learning for domain adaptation in the supervised classification of remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 11, pp. 4468–4483, Oct. 2012.

[68] W. Di and M. M. Crawford, "View generation for multiview maximum disagreement based active learning for hyperspectral image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 5, pp. 1942–1954, Apr. 2012.

[69] W. Di and M. M. Crawford, "Active learning via multi-view and local proximity co-regularization for hyperspectral image classification," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 3, pp. 618–628, June 2011.

[70] E. Pasolli, F. Melgani, D. Tuia, F. Pacifici, and W. J. Emery, "SVM active learning approach for image classification using spatial information," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 4, pp. 2217–2233, Mar. 2014.

[71] Z. Liu, W. Shi, D. Li, and Q. Qin, "Partially supervised classification based on weighted unlabeled samples support vector machine," *Advanced Data Mining and Applicat.*, vol. 3584, pp. 118–129, Aug. 2005.

[72] L. Bing, D. Yang, L. Xiaoli, L. W. Sun, and Y. Philip, "Building text classifiers using positive and unlabeled examples," in *Proc. 3rd IEEE Int. Conf. Data Mining*, Melbourne, Florida, 2003, pp. 179–186.

[73] H. Yu, J. Han, and K. C. C. Chang, "PEBL: Positive example based learning for web page classification using SVM," in *Proc. Int. Conf. Knowledge Discovery and Data Mining*, 2002, pp. 239–248.

[74] X. Li and B. Liu, "Learning to classify text using positive and unlabeled data," in *Proc. 18th Int. Joint Conf. Artificial Intelligence (IJCAI'03)*, 2003, pp. 587–592.

[75] L. Bruzzone, M. Chi, and M. Marconcini, "Transductive SVM for semisupervised classification of hyperspectral data," in *IEEE Int. Geosci. Remote Sens. Symp.*, Seoul, Korea, July 2005.

[76] 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.

[77] L. Bruzzone, M. Chi, and M. Marconcini, "Semisupervised
support vector machines for classification of hyperspectral remote sensing images," in *Hyperspectral Data Exploration: Theory and Applications*, C.-I. Chang, Ed. Hoboken, NJ: Wiley, 2007, pp. 275–311.

[78] B. Demir and S. Erturk, "Hyperspectral image classification using relevance vector machines," *IEEE Geosci. Remote Sens. Lett*, vol. 4, no. 4, pp. 586–590, Oct. 2007.

[79] G. M. Foody, "RVM-based multi-class classification of remotely sensed data," *Int. J. Remote Sens*, vol. 29, no. 6, pp. 1817–1823, Mar. 2008.

[80] R. Zhang and J. Ma, "An improved SVM method P-SVM for classification of remotely sensed data," *Int. J. Remote Sens*, vol. 29, no. 20, pp. 6029–6036, Oct. 2008.

[81] M. M. Dunder and D. A. Landgrebe, "A cost effective semisupervised classifier approach with kernels," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 1, pp. 264–270, Jan. 2004.

[82] L. Bruzzone and M. Marconcini, "An advanced semi-supervised SVM classifier for the analysis of hyperspectral remote sensing data," in *Proc. Soc. of Photo-Optical Instrumentation Engineers*, 2006.

[83] M. Chi, R. Feng, and L. Bruzzone, "Classification of hyperspectral remote-sensing data with primal SVM for small-sized training dataset problem," *Advances in Space Research*, vol. 41, pp. 1793–1799, Dec. 2008.

[84] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, Sept. 2001.

[85] J. A. Dare, "Support vector machines in a binary hierarchical classifier," M.S. thesis, Univ. Texas at Austin, 2004.

[86] Y. Chen, M. Crawford, and J. Ghosh, "Integrating support vectormachines in a hierarchical output space decomposition framework,"in *Proc. IEEE Int. Geoscience Remote Sensing Symp.*,Alaska, 2004.

[87] M. Chi and L. Bruzzone, "Semisupervised classification of hyperspectral images by SVMs optimized in the primal," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 6, pp. 1870–1880, June 2007.

[88] D. Zhou, J. O. Bousquet, T. Navin Lal, J. Weston, and B. Scholkopf,"Learning with local and global consistency," in *Advances in Neural Information Processing System*, Cambridge, MA: MIT Press, vol. 16, pp. 321–328, 2004.

[89] L. Gomez-Chova, G. Camps-Valls, J. Munoz-Mari, and J. Calpe, "Semi-supervised cloud screening with Laplacian SVM," in *IEEE Int. Geoscience Remote Sensing Symp.*, pp. 1521–1524, 2007.

[90] M. Belkin, P. Niyogi, and V. Sindhwani, "Manifold regularization: A geometric framework for learning from labeled and unlabeled examples," *J. Machine Learning Res.*, vol. 7, pp. 2399–2434, Oct. 2006.

[91] M. I. Jordan, *Learning in Graphical Models*, 1st ed. Cambridge,MA: MIT Press, 1999.

[92] L. Gomez-Chova, G. Camps-Valls, J. Munoz-Mari, and J.Calpe, "Semisupervised image classification with Laplacian support vector machines," *IEEE Geosci. Remote Sens. Lett.*, vol.5, no. 3, pp. 336–340, July 2008.

[93] Y. Gu and K. Feng, "Optimized Laplacian SVM with distancemetric learning for hyperspectral image classification," *IEEE J.Sel. Topics Appl. Earth Observ. in Remote Sens.*, vol. 6, no. 3, pp.1109–1117, May 2013.

[94] G. Camps-Valls, L. Gomez-Chova, J. Munoz-Mari, and J. Calpe, "Composite kernels for hyperspectral image classification,"*IEEE Geosci. Remote Sens. Lett.*, vol. 3, no. 1, pp. 93–97,Jan. 2006.

[95] T. Joachims, N. Cristianini, and J. Shawe-Taylor, "Compositekernels for hypertext categorization," in *Proc. Int. Conf. MachineLearning*, 2001, pp. 250–257.

[96] M. Marconcini, G. Camps-Valls, and L. Bruzzone, "A compositesemisupervised SVM for classification of hyperspectral images,"*IEEE Geosci. Remote Sens. Lett.*, vol. 6, no. 2, pp. 234–238,Mar. 2009.

[97] L. Bruzzone and C. Persello, "A novel context-sensitive semisupervisedSVM classifier robust to mislabeled training samples,"*IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 7, pp. 2142–2154,July 2009.

[98] D. Tuia and G. Camps-Valls, "Semisupervised remote sensingimage classification with cluster kernels," *IEEE Geosci. RemoteSens. Lett.*, vol. 6, no. 2, pp. 224–228, Apr. 2009.

[99] D. Tuia and G. Camps-Valls, "Urban image classification withsemisupervised multiscale cluster kernels," *IEEE J. Sel. TopicsAppl. Earth Observ. in Remote Sens.*, vol. 4, no. 1, pp. 65–74, Mar.2011.

[100] L. Huo, P. Tang, Z. Zhang, and D. Tuia, "Semisupervised classificationof remote sensing images with hierarchical spatial similarity," *IEEE Trans. Geosci. Remote Sens. Lett.*, vol. 12, no. 1,pp. 150–154, Dec. 2015.