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A VECTOR MACHINE BASED APPROACH TOWARDS OBJECT ORIENTED CLASSIFICATION OF REMOTELY SENSED IMAGERY

Pattathal Vijayakumar Arun[1], Sunil Kumar Katiyar[2]

[1]Ames center, NASA, California, USA
[2]Maulana Azad National Institute of Technology, Bhopal, India
E-mail: [1]arun.p.1988@ieee.org (corresponding author)

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Abstract: Remote sensing techniques are widely used for land cover classification and related analyses; however the availability of high resolution images have limited the accuracy of pixel based approaches. In this paper, we have analyzed the feasibility of incorporating contextual information to a support machine and have evaluated its performances with reference to the traditional approaches. We have adopted certain automatic approaches based on advanced techniques such as Cellular Automata and Genetic Algorithm for improving effective overlap between classes. Proposed methodology has been evaluated in comparison with the conventional approaches with reference to the study area using relevant statistical parameters. Accuracy improvement of the proposed approach may be attributed to the effectiveness in combining spatial and spectral information.

Keywords: classification, object based approach, support vector machine.

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Introduction

Land cover plays a pivotal role in impacting and linking many parts of the human and physical environments, hence monitoring its changes is highly significant. Remote sensing techniques are widely used for land cover classification and urban analyses. The accuracy of pixel based classification approaches are getting affected due to the increased resolution of satellite images and object based strategies are being devised as an alternative (Vapnik 1998). Literature reveals a great deal of advanced methodologies in this context; however these approaches may be further improved with the incorporation of more object specific parameters (Srivastava 2004; Schnitzspan *et al.* 2008). The spectral and spatial information can be combined to increase the seperability between classes to yield higher classification accuracy (Hosseini, Homayouni 2009).

Vector Machines (VM) along with mercer kernels have been widely used for the classification of multispectral as well as hyper spectral images (Tan *et al.* 2011; Schnitzspan *et al.* 2008). The technique constitutes of finding an optimal separation between the classes and also uses kernel method to project linearly inseparable data to a higher dimension space. Kernel methods have useful properties which facilitate the separation of even closely related classes, using a low number of (potentially high dimensional) training samples (Mercier, Lennon 2003). The existing VM based approaches do not consider the spectral meaning and behavior of the data, but instead rely on geometric measures for class separation (Schnitzspan *et al.* 2008). Mercier, Lennon (2003) proposed the linear mixing of quadratic with spectral kernels (Spectral Information Divergence& Spectral angle based) to achieve better classification results as compared to the statistical based approaches. Yanfen Gu *et al.* (2007) suggested soft classification of hyper spectral imagery by incorporating spatial and spectral information using composite kernel. However most of the object specific interpretation parameters have not been considered in these approaches. We propose a composite kernel strategy to analyze the spatial features along separate spectral bands, hence combining the spectral and spatial information for effective interpretation.

We have also investigated to augment vector machine based approaches with the incorporation of object specific interpretation keys such as shape and texture. Support vector machine (SVM), the commonly used vector machine, is an Independent and Identically Distributed (IID) classifier that does not consider interactions of adjacent data points; but have appealing generalization properties (Hosseini, Homayouni 2009; *Huang et al.* 2002). Support Vector Random Fields (SVRF) are Conditional Random Field (CRF) based extensions of vector machines that facilitate to better model the adjacency interactions (Chi-Hoon *et al.* 2005). SVRF model is robust to class imbalance, can be efficiently trained, converges quickly during inference, and can trivially be augmented with kernel functions to improve results (Lee *et al.* 2005). SVRFs have appealing generalization properties of SVMs along with the spatial dependency modelling capabilities of CRFs. We investigate to incorporate contextual parameters on SVRF variation of vector machines since it provides flexibility for effective augmentation (Melgani, Bruzzone 2008).

We have adopted a hierarchical SVRF approach (Gustavo, Luisel 2006) that incorporates SVMs along with multilayer CRFs in a consistent framework, in order to automatically model the optimal interplay between local, semi-local and global feature contributions. Proposed approach considers feature shape along with other interpretation keys and hence misclassification of objects under due to illumination variance may be avoided. We have used evolutionary computing approaches such as Cellular Automata (CA) as well as Genetic Algorithm (GA) for enhanced feature modeling.

In this paper we propose a vector machine based frame work for the incorporation of object specific interpretation keys to facilitate effective classification of spatial images. We have also adopted adaptive kernel strategy in which the kernel parameters have been adjusted with reference to the ensemble distributions. Different existing approaches along with the proposed approach have been evaluated with reference to the study area.

1. Theoretical background

1.1. Random modelling techniques

Evolutionary computing approaches such as CA, GA and their variants such as Cellular Neural Network (CNN) and Multiple Attractor Cellular Automata (MACA), have been found to be useful for modelling random features (Mitchell et al. 1996; Mnih, Hinton 2010). CNN is an analogue parallel computing paradigm defined in space and is characterized by the locality of connections between processing elements (Orovas, Austin 1998). Cell dynamics of this continuous dynamic system may be denoted using ordinary differential equations as given in equation (1), where vector G is the gene which determines the random nature.

$$X_k(t) = -X1 + f(G, Y_k, U_K). \qquad (1)$$

CNN is effectively used for modelling object shape to facilitate the incorporation of feature specific information in to the SVRF kernels. Random rules governing the shape of a feature can be identified by evolving the feature from a single state using CNN and GA. Abstract representations of objects are obtained by evolving features continuously until they can be separated from the background.

1.2. Vector machines

N-Dimensional classifiers such as VMs are non-probabilistic binary linear classifiers that constructs a set of hyperplanes to optimally separate the classes (Melgani, Bruzzone 2004). SVRF is a CRF based extension for SVM (Chi-Hoon *et al.* 2005; Lee *et al.* 2005). It considers interactions in the labels of adjacent data points while preserving the same appealing generalization properties as support vector machine (SVM) (Lennon *et al.* 2007). SVRF may be mathematically represented using equation (2) where $O(y_i, i(X))$ is an SVM-based Observation-Matching potential and $V(y_i, y_j, X)$ is a (modified) DRF pair wise potential:

$$P(Y \mid X) = \frac{1}{Z}\exp\left\{\sum_{i\in S}\log(O(y_i,\Gamma_i(X))) + \sum_{i\in S}\sum_{j\in N_i} V(y_i, y_j, X)\right\}. \qquad (2)$$

The observation-matching function captures relationships between the observations and class labels, whereas local-consistency function models relationships between neighboring data points. SVRF is used along with the kernel functions to implement effective segmentation augmented with contextual knowledge.

1.3. Kernels

Kernels augment vector machines in measuring the similarity between two data points that are embedded in a high, possibly infinite, dimensional feature space (Mercier, Lennon 2003; Gustavo, Luisel 2006). Adaptive kernel strategy is implemented Mixture Density Kernel (MDK) that measures the number of times an ensemble agrees that two points arise from same mode of probability density function (Srivastava 2004). Mixture density kernels are used to integrate an adaptive kernel strategy to the SVRF based clustering as they facilitate learning of kernels directly from image data rather than using a static approach.

The composite kernel concept is used to incorporate spectral and spatial information, given $X = \{x_1, x_2, ..., x_m\}^T$ be the spectral characteristics of an M-band multispectral imagery and $Y = \{y_1, y_2,..., y_n\}^M$ be the spatial characteristics, then the possible spectral and spatial kernel $K_x(P,P_i)$ <Φ(P), Φ (P_i)>, $K_y(P,P_i)$ < Ψ (P), Ψ (P_i) respectively. Preferably a weighted combination of the kernels are adopted as discussed in (Gustavo, Luisel 2006) such that $K(P,P_i)$ $\mu K_x(P,P_i)$ $(1-\mu)K_y(P,P_i)$ nd the value of tuning parameter is adjusted with respect to the objects.

2. Experiments

2.1. Data

Proposed approach has been evaluated over multispectral LISS III and LISS IV sensors images of Indian Remote Sensing Satellites and details are given in Table 1.The image has been geo referenced using ERDAS 9.1 and has been sub set for the Bhopal Area. The study area constitutes of five land cover classes namely agriculture, urban, barren, water, and forest. Study area is so selected that the spatial distributions as well as area fraction of almost all classes are uniform and hence the effect of these factors over classification accuracy is made negligible.

The ground truthing has been done using Differential Global Positioning System (DGPS) survey data collected over the study area using Trimble R3 DGPS equipment with centimeter level accuracy. Details of the data are presented in Table 2.

2.2. Proposed algorithm

The schematic representation of the proposed algorithm is as given in the (Fig. 1). During training phase, first the edges are detected using Canny operator, then a CA based region growing strategy is adopted to approximatelyextract the objects. Each pixel is assigned a state, namely 'B' for boundary pixel, 'NB' for non boundary pixel and 'NR' for non region pixels. Initially boundary pixel states are assigned as 'B' and non boundary pixel states as 'UB'. The 'NB' pixel state is changed to 'NR' iteratively if it is near to a boundary pixel. The whole procedure is repeated until no further state change is experienced, thereby detecting different objects in the image. Further CNN along with GA is used to find rules that iterate from a given initial state

Table 1. Details of experimental data

S. No.	Imaging sensor	Spatial resolution(m)	Satellite	Area	Date of acquisition
1	LISS-III	23.5	IRS-P6	Bhopal(India)	5th April 2009
2	LISS-IV	5.6	IRS-P6	Bhopal(India)	16th March2010

Table 2. Ground truthing information

S.No	Area	Date of procurement	No. Classes	No .of points / class	Accuracy
1	Bhopal	November, 2012	5	40	cm level (10^{-2})

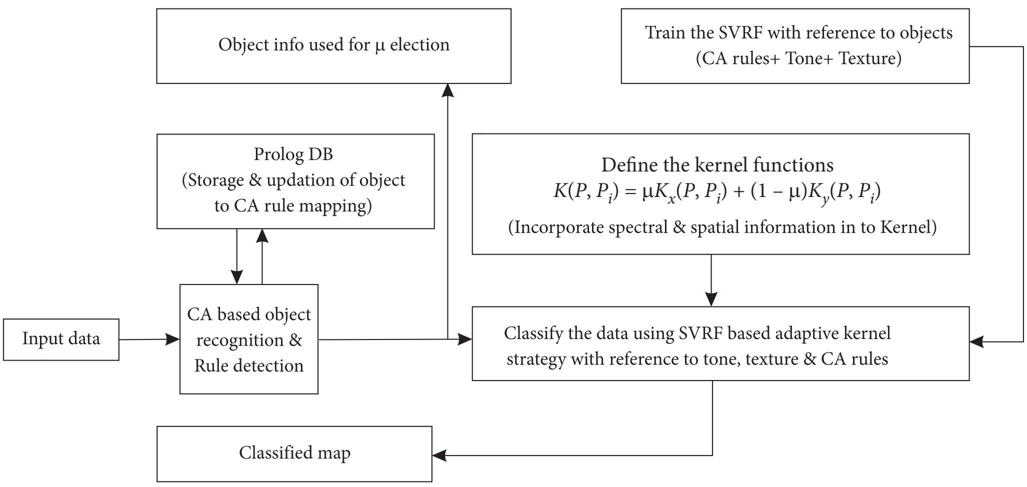

Fig. 1. Proposed algorithm

to a desired final state. This inverse mapping or evolution is exploited to model feature shapes, and CNN rules used to evolve a particular feature are used to distinguish it. These extracted rules reveal the shape information of various features and are used for classification along with other interpretation keys.

In the validation phase, SVRF uses training samples to classify the input image where tone, texture and CA rules are adopted for an effective approach. Kernel parameters are adjusted from an ensemble of probabilistic mixture models, where each model is generated from a Bayesian mixture density estimate. Features are calculated along each band and composite kernel strategy is used to incorporate these spectral and spatial information where tu μ is adjusted based on the object nature.

2.3. Implementation

The algorithms have been implemented in MATLAB and were compared with the commonly used conventional approaches. Relevant statistical parameters such as *Overall Accuracy* (Mnih, Hinton 2010) and *Kappa* Coefficient of agreement (Melgani, Bruzzone 2008; Nasset 1996) have been used for comparative evaluation. The procedure of accuracy estimation is as summarized in (Fig.2).

3. Results and discussions

The investigations of this research work revealed that augmentation of vector machine based classification scheme with feature specific parameters and spectral information reduces false alarms for thematic classification. For instance, recreational forest area (VanVihar national park- Bhopal), which has been difficult to classify due to small trees and shadows, has been correctly classified with the approach. Efficiency of the approach with reference to traditional classifying techniques has been evaluated using various statistical measures and results are as summarised in Table 3.

Investigation results reveal that the classification accuracy of traditional methods has been affected due to the increase in resolution of satellite images. This is evident from the lower accuracy of these methods over

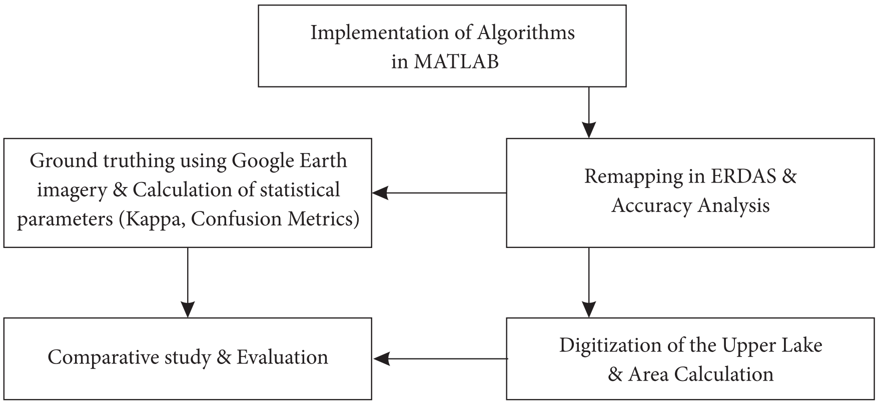

Fig. 2. Accuracy Analysis

Table 3. Results of accuracy analysis

S. No	Sensor	Methodology	Kappa statistics	Overall accuracy (%)
1	LISS 3	Mahalanobis	0.88	86.13
2	LISS 3	Minimum Distance	0.91	87.58
3	LISS 3	Maximum Likelihood	0.91	89.83
4	LISS 3	Parrellelepiped	0.93	92.81
5	LISS 3	Feature Space	0.94	92.85
6	LISS 3	SVM(Spectral & spatial factor considered)	0.97	96.92
7	LISS 3	SVRF(Spectral & spatial factor considered)	0.98	97.81
8	LISS 4	Mahalanobis	0.85	84.40
9	LISS 4	Minimum Distance	0.89	85.00
10	LISS 4	Maximum Likelihood	0.88	86.80
11	LISS 4	Parrellelepiped	0.90	88.62
12	LISS 4	Feature Space	0.92	90.56
13	LISS 4	SVM(Spectral & spatial factor considered)	0.98	97.84
14	LISS 4	SVRF(Spectral & spatial factor considered)	0.99	98.89

LISS 4 image when compared to LISS 3. Accuracy of the proposed approach has been found to be comparatively stable over the change in resolution and has also found to perform better. Higher values of kappa and over all accuracy indicate that the proposed algorithm is giving better results at every resolution. Performances of the proposed & SVM based approaches are similar for lower resolution data (say LISS 3) since the differences in performance is the effect of object specific parameters which are relatively less achievable at lower resolution.

The performances of these methodologies have been also evaluated by comparing areal extents of various features. The features having well defined geometry like lakes, parks etc have been selected for comparative analysis vector machine based classification. The original surface areas of the features are calculated by manual digitization using ERDAS and comparative the results are presented in Table 4. Comparative analyses of the areal extents also indicate that the SVRF approach yields better results compared to the

Table 4. Comparison of the geographical extent of various features

S.No	Sensor	Feature	Reference area (km^2)	Methodology	Areal extent (km^2)
1	LISS3	Lake	32.5	Mahalanobis	25.42
				Minimum Distance	24.31
				Maximum Likelihood	27.37
				Parallelepiped	28.58
				Feature Space	26.82
				SVM(Spectral & spatial factor considered)	28.71
				SVRF(Spectral & spatial factor considered)	30.72
2	LISS3	Parks	2.13	Mahalanobis	0.82
				Minimum Distance	0.89
				Maximum Likelihood	1.45
				Parallelepiped	1.37
				Feature Space	1.51
				SVM(Spectral & spatial factor considered)	1.58
				SVRF(Spectral & spatial factor considered)	1.65
3	LISS3	Artificial Forest area (Vanvihar)	4.41	Mahalanobis	–
				Minimum Distance	–
				Maximum Likelihood	–
				Parallelepiped	–
				Feature Space	–
				SVM(Spectral & spatial factor considered)	2.61
				SVRF(Spectral & spatial factor considered)	3.52
4	LISS4	Lake	32.81	Mahalanobis	24.31
				Minimum Distance	23.40
				Maximum Likelihood	25.12
				Parallelepiped	26.24
				Feature Space	27.17
				SVM(Spectral & spatial factor considered)	29.43
				SVRF(Spectral & spatial factor considered)	31.08
5	LISS4	Parks	2.37	Mahalanobis	0.51
				Minimum Distance	0.72
				Maximum Likelihood	1.53
				Parallelepiped	1.14
				Feature Space	1.46
				SVM(Spectral & spatial factor considered)	1.63
				SVRF(Spectral & spatial factor considered)	1.71
6	LISS4	Artificial Forest area (Vanvihar)	3.95	Mahalanobis	–
				Minimum Distance	–
				Maximum Likelihood	–
				Parallelepiped	1.81
				Feature Space	–
				SVM(Spectral & spatial factor considered)	3.42
				SVRF(Spectral & spatial factor considered)	3.62

other methods. The VanVihar national park which is a recreational forest area has been distinguished using the proposed approach and this indicates superiority of this method for object based classification.

Table 5. Analysis of spatial & spectral considerations over classifier

S. No	Sensor	Methodology	Kappa statistics	Overall accuracy (%)
1	LISS 3	SVM (spatial)	0.94	89.13
2	LISS 3	SVRF (spectral)	0.72	70.21
3	LISS 3	SVM (spectral+spatial)	0.97	96.92
4	LISS 3	SVRF (spectral+spatial)	0.98	97.81
5	LISS 4	SVM (spatial)	0.95	91.08
6	LISS 4	SVRF (spectral)	0.75	74.07
7	LISS 4	SVM (spectral+spatial)	0.98	97.84
8	LISS 4	SVRF (spectral+spatial)	0.99	98.89

The classified results for the LISS 3 imagery using various methodologies are as given in (Fig. 3) and visual interpretation also reveals the accuracy of SVRF based methodology.

We have also investigated the effect of spectral considerations with reference to vector machine approaches and results are summarized in Table 5. It has been found that the spectral and spatial considerations separately do not yield good results and spectral considerations alone have the worst. However when combined together as proposed it results in a significant improvement in the accuracy.

Investigations have revealed that the support vector based approaches (SVRF&SVM) outperforms conventional counterparts and that the proposed method is performing better. The main disadvantage of the suggested approach is its computational complexity which can be improved using coreset optimization and similar approximation techniques. Complexity can be further reduced by storing the detected rule variations; optimization methods such as GA can be

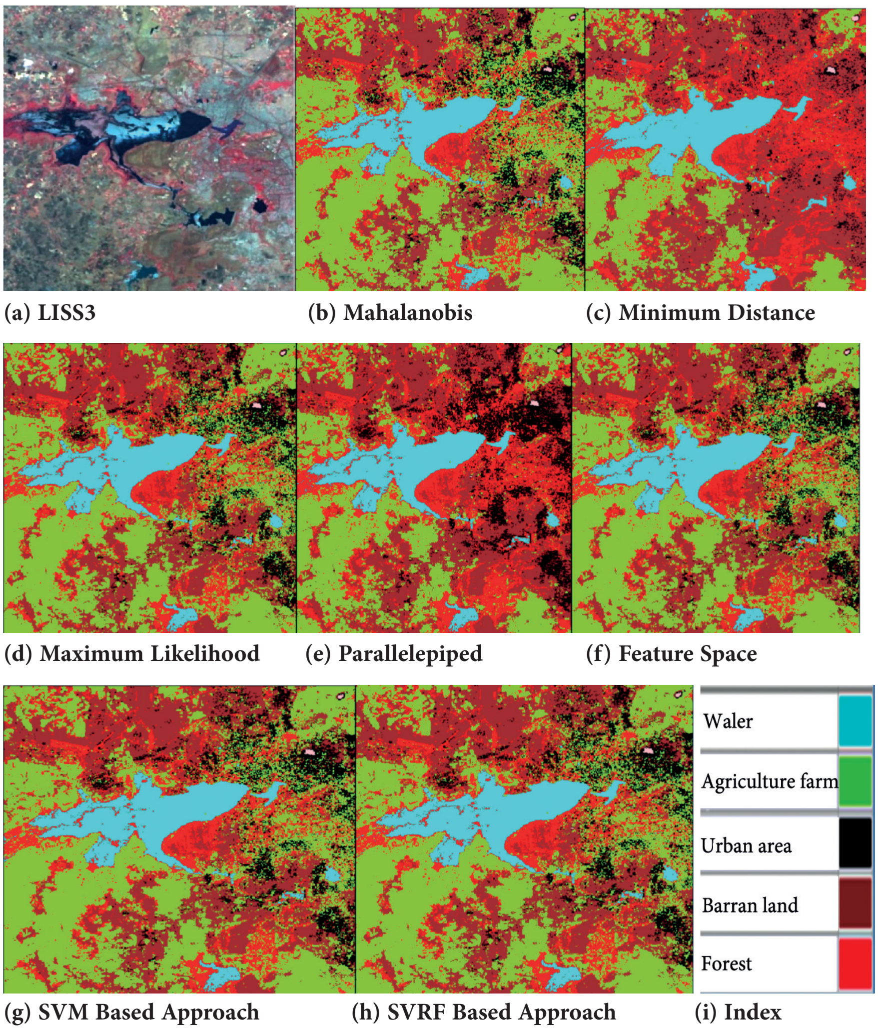

Fig. 3. Visual comparison of different Classification method results for LISS3 sensor imagery

exploited to optimize the strategy. This research provides a basic framework and further investigations are needed to enhance it. Integration of a fuzzy approach to the inverse mapping also seems to be promising, since fuzzy / neutrosophic cognitive maps can be exploited for effectively organizing and selecting CA rules.

Conclusions

Vector machine based approaches have found to give better results when augmented with probabilistic approaches like CRF, since the spatial dependencies between classes have been taken in to consideration. The investigation revealed that use of spectral knowledge along with object specific parameters into SVRF classification reduces false alarms for thematic classification. The proposed use of CA for the incorporation of feature specific rules has found to yield better results. SVRF based approach is found to outperform the contemporary methods and can be made semi supervised by enhancing with Learning Automata. We have presented the basic framework which needs further improvement for effective use.

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Pattathal Vijayakumar ARUN. He has completed his Masters from NIT-Bhopal, and is currently pursuing PhD. His main area of interest are artificial Intelligence, spatial mining, and image processing.

Sunil Kumar KATIYAR is a Professor as well as Chairman of Remote Sensing Center at Maulana Azad National Institute of Technology, Bhopal. He is a countable expert in the field of remote sensing with years of experience in the field. His area of interest include image processing, GPS, and Cartography. He had served as the PI in several national and international projects.