ISSN: 2393-8528

Contents lists available at www.ijicse.in

International Journal of Innovative Computer Science & Engineering

Volume 3 Issue 2; March-April-2016; Page No. 01-08

Optimized Feature Selection for SVM based Crop Classification using Multi-spectral Remote Sensing Images

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ARTICLE INFO

Received: 17 March. 2016
Accepted 30 March 2016

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Keywords: *Acreage, classification, crop, evolutionary algorithms, features selection, multi-spectral, optimization, remote sensing, satellite image*

ABSTRACT

Feature extraction directs the classification process for any sort of data, may be textual database, simple image or complex geo-tiff images procured using remote sensing technology. In spite of, numerous features that identified for usual textual data types used by researchers across the globe, more complex, but specific features are needed for classifying satellite images with special emphasis upon agricultural crops because of the challenge to discriminate it from customary surrounding vegetation. Identification of such more relevant features pertaining to remote sensing data in order to estimate its crop acreage will be the great for computer professionals and researchers. Once the features are collected, finding the best amongst them, will the second priority task towards classifying crops. Scientist came up with the concept of feature dimension reductionality in order to decide upon the section of best features for problems in hand. Evolutionary algorithms have proven to be the best for such problems, even in remote sensing domains. Further, its application may be extended towards optimization of best features for crop classification based on SVM using multi-spectral remote sensing images.

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1. INTRODUCTION

Satellite images are very complex and heterogeneous in nature. It is easy to extract trainings samples from same region of interest and test the same image for classification problem accurately. However, it is challenging task to collect training samples (in terms of pixel values) from one satellite image and apply it to any other satellite image for given classification problem. This could be achieved by virtue of range processing concept, where range of pixels were collected from various regions or even image samples and check for its pixels purity index for specific crop classification. A concept of dynamic range processing may even applied to test the effect on classification accuracy. Across globe, many researchers attempted to create spectral library (based on wavelengths) for many of the vegetation species. But, this is unique attempt to create pixel library (based on DN values) in order to classify specific crop type from multi-spectral satellite images. Even, this study can be further expanded for multiple crop types or even many other vegetation species of interest.

Multispectral remote sensing is the collection and analysis of reflected, emitted, or back-scattered energy from an object or an area of interest in multiple bands of regions upon the electromagnetic spectrum. Other variant of remote sensing data is the Hyperspectral imaging, in which hundreds of bands are collected and analyzed, and ultra spectral remote sensing where wide variety of bands are used . Last but not the least, Microwave remote sensing deals with polarization technique for classifying the images, even taken in cloudy conditions. [26]

The main advantage of multispectral imaging is the potential of color channels to classify the image using supervised classification approach. This is much faster method of image analysis as compare to visuals interpretation, Remote sensing image classification has been widely applied in many fields such as natural resource exploration, agricultural area monitoring, urban planning, and disaster management. This research is going to focus on classifying agricultural areas using multispectral satellite data. A multispectral image is one that captures image data at specific frequencies across the electromagnetic spectrum. Multispectral images are acquired by means of remote sensing radiometers or sensors. Dividing the spectrum into many bands, multispectral is the opposite of panchromatic, which records only the total intensity of radiation falling on each pixel. Usually, satellite images captured in three or more channels. Each one used for acquiring single digital image in a small band of visible spectra, ranging from 0.7 µm to 0.4 µm, called red-green-blue (RGB) region, and going to infrared wavelengths of 0.7 µm to 10 or more µm. Remote Sensing Images are considered as most complex in nature as regards to image classification. Supervised classification of Remote Sensing Images needs more precise machine learning models, in terms of time and space complexity. [5][24-27]

IRS-P6 ResourceSat-1 is intended to continue the remote sensing data service with the improved spatial resolution. ResourceSat-1 carries three cameras: Linear Imaging and Self Scanning Sensor (LISS-3), a high resolution Linear Imaging Self Scanner (LISS-4), which allows the acquisition of stereoscopic imagery, and an Advanced Wide Field Sensor (AWiFS) {et al. NRSC}

TABLE 1: IRS P6 MULTISPECTRAL IMAGES SPECIFICATIONS

IRS P6 Sensors	Multi-spectral Image Specifications			
	Swath	***Spatial Resolution***	***Radiometric Resolution***	***Revisit Time***
AWiFS	740 km at nadir	56 m	10 bits per pixel	5 days
LISS-3	141 km at nadir	23.5 m	7 bits per pixel	
LISS-4 MX	23.9 km at nadir	5.8 m	7 bits per pixel	5 days
LISS-4 PAN	70.3 km at nadir	5.8 m	7 bits per pixel	5 days

Multi-spectral bands and respective spectral ranges:
0,52 – 0,59 µm (band 2 – Green)
0,62 – 0,68 µm (band 3 – Red)
0,77 – 0,86 µm (band 4 – NIR)
1,55 – 1,70 µm (band 5 – SWIR) only for LISS-3 and AWiFS)

It is suggested to identify different crop types so as to estimate its crop acreage, which could be the foremost step towards crop monitoring. Considering the limitations of traditional crop survey methods regarding malfunctions or delayed information compilation, remote sensing image analysis could be the effective way to overcome this problem. Multi-spectral images have features that could be most useful in agriculture domains, viz. synoptic coverage, seasonal information availability, strong spatial heterogeneity, outreach to inaccessible areas, etc. Since improvement in technology and theory have been in continuously evolving, the achievements are remarkable in using remote sensing data for crop identification and area estimation [5].

In this paper, the section II explains about significance of SVM in classifying multi-spectral remote sensing image. Section III explains about details of multi-spectral feature selection and extraction and section IV illustrate effect of feature optimization techniques upon classification accuracies, and finally concluded with outreach of this article.

2. **Svm based Satellite image classification**

The satellite sensor system normally records the reflected or emitted radiant flux from heterogeneous mixtures of biophysical material such as soil, water, and vegetation. With this effect, natural features usually mixed into one another without sharp, hard boundaries. Thus, real world information on ground is very imprecise and heterogeneous in nature. Perhaps, each pixel may contain heterogeneous information and hence encounter the problem of mixed pixel and hence areas are estimated incorrectly from Remote Sensing Images. It is obvious from studies of various scientists that Machine Learning approach like Support Vector Machine (SVM)[30] is giving good performance in order to address this mixed pixel issue in event of thick vegetation around agricultural area.

Since the last decades, SVMs is more referable for various classification problems due to its flexibility, computational efficiency and ability to handle high dimensional data [3,4]. Therefore, classification of image should be done using SVM (Support Vector Machine) because it is proven through studies to be one of the best classifier as compare to other (like neural network algorithm, fuzzy logic etc.). Researchers examined hyperspectral images by applying machine learning algorithms like Maximum Likelihood, Decision Tree, Artificial Neural Network and Support Vector and also tested sub-pixel classification algorithms like LMM, ANN, & SVM for its behavior on effect of dimensionality of feature space, effect of training sample size, and number of bands used to achieve better classification accuracy. The finding of their research illustrate that upcoming statistical learning classifier SVM produces the best accuracies as compared to other algorithms, even if number of bands increases to more than 100. [28]. SVM was further tested with special context to agricultural applications, using its different kernels, it was obvious that Sigmoid kernel perform better than other SVM kernel like Polynomial, Radial Basic, and Linear kernel for definite training data size. Further, it was concluded that no reduction in classification accuracies observed as the number of bands was increased even if training samples is small. In a nutshell, it is observed from various studies that classification accuracy depends on parameters like nature/number of training samples, number of bands used, number of classes to be identified, properties of classification algorithms, and optimum parameters of classification algorithm[25]

A. Effect of Contextual features on Support Vector Machine

It is assumed that geographical phenomenon generally display an order or structure such that certain features on land are likely to occur in context of others. The statistical dependence between pixel is defines by neighborhood system. It is assume that physical properties in neighboring system do not change dramatically and it has some coherence over that space. (Forest changes gradually into grassland, not abruptly) Hence, concept of Contextual Classification chip in with the problem of incorporating contextual information expressed in terms of spatial relations that exist between one pixel and pixels in rest of the image.

With reference to the literature worldwide, Support Vector Machine (SVM), a machine learning algorithm has proved to be an excellent algorithm for Classification of Remote Sensing Images, even though it is complex in nature. As we know that SVM is basically a binary classifier, which is non-parametric in nature [30]. It will be interesting to make an attempt to evaluate effects of various contextual information on performance of SVM. It is learnt that there exists various parameters influencing accuracy of soft classification viz. nature and number of training samples, number of bands used, number of classes to be identified, properties of classifiers, optimum parameter of classification algorithm, contextual information incorporated, etc., out of which contextual information is one of the crucial part that affects the accuracy of remote sensing images. We need to address this issue in our project so as to devise noble algorithm or approach, which could make SVM, a more robust statistical learning model. There are several contextual classifiers available like Markov Random Field (MRF classifiers), Discriminative Random Field (DRF classifiers), Spatial AdaBoost classifier, Spatial Auto-regression (SAR Classifiers), Expectation Maximization (EM classifier), Maximum a Posterior (MAP classifier) [26]. We will focus on studying all those and find out which one is best suited for which kind of feature classification. Moreover, we may devise a new one by combining strength of each one of them in order to get accuracies at par.

On the other hand, SVM used for the estimation of probability density functions [24] with the help of easy and efficient machine learning procedures based on Mean Field theory. Density estimation based SVM approach uses fuzzy weighted matrices to define fuzzy kernels like Linear, Polynomial Radial Basic, and Sigmoid along with various norms viz. Euclidian norm, Diagonal norm, and Mahalonobis norm. Mahalonobis norm is suitable for Forest mapping, whereas Diagonal norm gives best results for Agricultural and Fallow Land mapping. While modeling the spatial contextual information for hard classifiers using Markov Random Field it has been found that Metropolis algorithm is easier to program and it performs better when compared with the Gibbs sampler. In study, it has been found that in case of soft contextual classification Metropolis algorithm fails to sample from a random field efficiently and Gibbs Sampler performs better than the Metropolis algorithm, due to high dimensionality of the soft classification output [25].

3. Multispectral image Feature extraction and selection

The studies found Image classification as much significant domain even today and it gives rise to exponential growth of image based data and its computer vision related applications viz. remote sensing, medical imaging, and face recognition [1]. However nobody achieves the ideal accuracies and it still remains as a multifarious task [2]. Traditionally, image classification is utilizing one of the rigidly formal classification algorithms such as Support Vector Machines (SVM) and Decision Trees on extracted features that achieved as a result of transformation from original image. The dimensionality of raw image data is generally too high for most classification problems. Hence, the feature extraction and feature selection phases are playing equally critical role in classifying images. The subsequent classification is directly affected by the extracted and selected features. Poor features would not lead to accurate classification, using irrelevant features also considerably increases the computation time. Too many features may render the convergence impossible, leading to random

Table 1:

S.N.	FEATURE NAME	TYPE
1	Border Index	Shape
2	Area	Size
3	Roundness	Shape
4	Brightness	Spectral
5	Shape Index	Shape
6	Mean Green	Spectral
7	Mean Red	Spectral
8	Mean NIR	Spectral
9	Compactness	Shape
10	SD of Green	Texture
11	SD of Red	Texture
12	SD of NIR	Texture
13	Length	Shape
14	Width	Shape
16	Rectangularity	Shape
17	Density	Shape
18	Asymmetry	Shape
19	NDVI	Spectral
20	Border Length	Shape
21	Entropy	Spectral
22	Height	Elevation
23	Shadow	Elevation
24	Leaf Area Index	Spectral
25	Slopes	Adjacency
26	Segmentation Scale	Temporal
27	Connectivity	Adjacency
28	Roughness	Texture
29	Edge pixel	Adjacency
30	Crop age	Temporal

Classification decisions. Therefore, efficient feature optimization techniques are severely needed for accurate image classification across several applications.

Feature selection task and features extraction task have great significance in many fields including remote sensing, face recognition, image processing etc. For agricultural field among all general features, it needs very specific features to be selected for crop identification. The more relevant features that applicable to agriculture domain are shape feature, texture feature, shadow, spectral and special features, local feature, region of interest extraction [6,7,8,9,10,11]. Other features we are focusing are size, entropy, dryness, vector mask, vegetation indices, pattern, color etc.

Utility of multi-sensor multi-spectral images from Resourcesat-1 was evaluated for discrimination of crops by virtue of selecting optimal monochromatic band of LISS 4 data so as to merge it with LISS 3 data. Performance of each band of LISS-4 sensor is evaluated against various data fusion techniques and concluded that red band is most suitable for data fusion. Among the five methods evaluated, the wavelet method found to be superior for visual interpretability, image quality parameters and classification accuracy. The wavelet merged data was spectrally similar to L-3 data while maintaining spatial resolution of L-4 data enabling better discrimination of crops[23]

Features in general that were tested by Scientist for classifying images across variety of domains are; Spectral, Size, Shape, Texture, Pattern, Entropy, Color, etc. However, radiometry (bit depth), number of band, spatial resolution, and image heterogeneity area the major properties of multi-spectral remote sensing images that photogrammetric professionals usually considered for crop acreage estimation. Perhaps, the features like Vector mask, Vegetation Indices, Season, Crop Cycle, Dryness, LAI, etc. are of utmost importance for classifying crop in agricultural fields. During classification of remote sensing images for agricultural applications, every crop in agricultural field exhibits different properties, which may be considered as features for interpreting multi-spectral satellite images. For example, Gram can be identified in “smooth pinkish color”, Wheat as “dark red color”, Cotton is bit difficult to identify as it reflects mixed pattern of pixel values, whereas Sugarcane can be clearly seen in “magenta color”. Besides, there may be many more features that researchers across globe have applied in various agricultural applications. Following are the list of such features relevant to crop classification using remote sensing images;

From above tables, it is obvious that vegetation indices are prominent image features that closely pertinent to agriculture crop discrimination. It is a image enhancement technique which perform rationing of different band of different vegetation of same signature. It’s a band rationing technique. For example Vegetation Index (VI) = IR/R and its NDVI = (IR+R)/(IR-R). Vegetation Indices are important to remove effects of shadows, low luminosity, topographic effects and atmospheric effects in case of remote sensing data. For example, DN value of mango trees facing sun is different than those on other side of Hill. Due to low intensity mangoes in shadow could not be identified, hence need to normalize DN values of both cases so as to classify accurately. Some famous Vegetation Indices are NDVI (Normalized Differential Vegetation Index), TVI (Transformed Vegetation Index), SaVI (Soil-adjusted Vegetation Index), MSaVI (modified soil-adjusted vegetation index), etc. The research may be focused on study of all these indices and checks its performance for evaluating classification accuracies using remote sensing images.

Towards improvement in classification accuracy using VHR remote sensing imagery, mean shift vector-based shape feature (MSVSF) introduces by Rongjun Qin [6] which uses component analysis method to extract spectral feature and SVM classifier is adapted for classifying using these features and come up with novice feature based upon the experimental results. Feature extraction is done first on a predefined window and later local homogeneous/similarity area (LSA) technique is applied for enhancement [6]. It is concluded from the results that Mean Shift (MS) analysis has performed well and proved to be very effective for classifying the VHR multi-spectral imageries.

For recognizing the pattern or texture in images texture feature, Varadarajan and Karam [7] proposed a no-reference perceptual metric that predicts the grade of perceived regularity in textures. Moreover, researchers applied new technique, named as Visual Saliency Map (VSM) of a texture to compute objective texture regularity metric for the targeted texture feature. Texture identification as a features is been used to classify using remote sensing images. Habib and Inglada [18] present several feature selection algorithms in combination with SVM algorithm are classified into filter and wrapper approaches. Author used mutual information based technique for the filter based results, while the kernel properties provide better results for the wrapper based approaches.

Femiani, Razdan, and others [8] recently in May 2015 demonstrated shadow detection technique for detecting buildings and even its rooftops by adopting set of rules. Further, Grabcut algorithm is used to identify complete rooftop regions. Researchers in [8] initialize the algorithm to extract shadow and vegetation as done in [12] using a modified four band (RGB and NIR) version of Grabcut. Unlike [12], researchers author add corrections to the results wherever inconsistency with shadows in the image found until Grabcut converges to a segmentation that is consistent with the shadows. .

Zhong; Duan, and others [9] in May 2015, proposes spectral–spatial feature extraction method which used tensor representation for three spectral and spatial feature extraction methods as extended morphological profiles (EMPs) [13], extended attribute profiles (EAPs) [14], and Gabor filtering [15].Further, Local Tensor Discriminant Analysis (LTDA) technique is used to reduce the redundant information among these feature effectively and also extract discriminative features. This extracted feature representations are then rearranged back into vector representation for training SVM classifiers. Findings show that the methods with tensor representation achieve higher classification accuracy and better visual results.

Local Feature Detection (LFD) technique as introduced in [10] uses an object detection algorithm based on local features. LFD reduces complexity of processing, local feature description, and feature matching. Liao and Juba [10] used improved Harris Corner Selection strategy which searches only the corners near enhanced edges by using a z-score normalization. Afterwards, descriptor is constructed to represent these local feature points. Researchers introduces MSMF [17] descriptor by improving the descriptor which combines the SPIN [16] descriptor and the RIFT [17] descriptor in a unified framework. In this study, new methods were proposed for improving the efficiency of the feature matching using various descriptors.

A feature to extract region of interest (ROI) is proposed by Zhang and Li in [11] which uniformly highlighting entire ROIs, well-defined boundaries, and good stability against noisy data. In high spatial resolution remote sensing images ROI model is based on Salience Analysis of Co-occurrence Histogram (SACH), when tested qualitatively and quantitatively, outperform against the nine other models under study. The findings concluded that ROI model can extract entire highlighted ROIs with well-defined boundaries from high spatial resolution remote sensing images, even corrupted or free from noise. The researchers further illustrated that model is robust against input images with both Salt and Pepper noise and Gaussian noise.

4. **Features optimization techniques**

When features so extracted from multi-spectral satellite images are minimum as in case of LISS-IV, it is 3 features only in form of RGB bands, no need to for optimizing features as it may be possible even by applying heuristic approaches. But, as the number of features increases, the dimensionality of images also increases and it may the situation where we may need to select few of them. Hence, optimization techniques used to reduce the dimensionality of features space in classification problems. Optimal feature selection is a important but challenging task because selected features have direct impact on classification performance.

Classification accuracy can be improved recently in 2014 by Wu, Zhao, and others [19] by introducing Cramer's V-test, which optimally partitions the continuous features into discrete ones. Two association based feature selection indexes were proposed to select optimal feature subset; one is CVD based Association Index (CVDAI) and other is Class Attribute Interdependence Maximization (CAIM) Association Index (CAIMAI). J48 decision tree and Naïve bias (NB) classifiers are used to check the performance of this feature descretization. Inspecting upon multi-spectral high resolution images and two hyperspectral dataset, results shows that CVD based technique has better ability to generate descretization scheme. Further, feature selection indexes CVD-AI and CAIM-AI perform better than other feature selection method [19].

Akhtar and Nazir [20] proposed new method for crop classification that based on two transform method; one feature is Discrete Cosine Transform (DCT) and other Discrete Wavelet Transform (DWT) features. These features are extracted from crops and then classify each of them by using different classifiers. The accuracy of the DWT features is more precise as compare to the DCT features. The 10-folds cross validation for classification is used and tested using different classification algorithms like Neural Network, Naïve Bayesian, K – nearest neighbor, Support vector machine and Decision Tree. It is found that the accuracy of the k-nearest neighbor is the most efficient as compare to the other classifier, even if noisy data used is used for experiment.

Some applications may need large number of different features, which potentially implies that the search space is complex and highly dimensional [21]. Features dimensions can be reduce to only relevant features by using evolutionary approaches like Genetic Algorithm (GA). When performed experimentation using LandSat multi-spectral images, GA optimally performs well. Goodness of a feature is highly problem dependent and often domain dependent to address this issue [22]. Genetic Programming (GP) based image classification method uses two-tier GP that directly operate on raw pixel rather than features. First tier in a classifier is for automatically defined features based on raw image input and the second make decision. It is noted that based on raw feature rather than predefine feature two tier GP achieve better accuracy on the range of tasks. When compared with the conventional approach like Naive Bayes, Decision Tree, SVM and then GP itself. The results show that the Two-Tier representation is valid and can outperform all these four classifiers on majority of tasks that performed on image.

5. Conclusion

In many ways, it is of utmost important to know exact land area covering agricultural crops. It is useful for giving compensations in event of crop damage due to flood, hailstorms, or any other natural calamity conditions. Moreover, it will be of immense use in case of Metro Region Planning in order to know how much area of Agricultural land goes into urbanization and loss on agricultural productivity arising thereof. Ultimately, it will effect on Government Policies deciding upon the rates of any of the commodities based on agricultural production. Hence, this topic of research is of highest importance, challenging, and motivation too. Feature optimization techniques were contemplated for improving performance of SVM towards estimation of agricultural crop acreage and suggest which features exactly & most appropriately utilized so as to accurately classify the crop in agriculture fields.

SVM is used to locate optimum boundaries between classes, which in return generalize to unseen samples with least error among all possible boundaries separating two classes.SVM uses density estimation function for developing easy and efficient learning parameters. Like other supervised algorithms, SVM also undergoes into Training, Learning, Testing, and Validation Phase for classifying any image. Besides all parameters, training feature selection and optimization is crucial part that affects the classification accuracy of remote sensing images. SVM were originally designed for binary classification, because of its definition, this classifier is expected to generalize accurately on unseen cases as compared to other classifiers. This will depend upon the how relevant features been extracted and optimized SVM performance for targeted crops.

Feature extraction is important task for classifying complex images like Remote Sensing Images collected through satellites. Many research in this field carried out as described earlier. Some recent optimizations techniques like are done by various authors. There are different algorithms, methods or techniques are proposed for optimal feature selection for doing any specific task.

Literatures exhibits more prominent crop inclined features like Vector mask, Vegetation Indices, Season, Crop Cycle, Dryness, LAI, etc. that are of utmost importance for classifying crop in agricultural fields. Vegetation indices could also be the good source for features selection as NDVI has proven records for enhancing images before classification. Researchers across globe invented the most distinguished feature extraction and selection techniques like Mean Shift Analysis, Visual Saliency Map, Local Similarity Area, extended morphological profiles, Local Tensor Discriminant Analysis (LTDA), Local Feature Detection, MSMF ,Salience Analysis of Co-occurrence Histogram, etc. which really outperforms as compare to other methods. In event of high dimensionality of features for multi-spectral satellite images, feature optimization is the only solution that accelerates the SVM performance. The most notable methods for feature optimization are CAIM-AI, DCT and DWT. Last but not the least, the use of evolutionary methods like Genetic Algorithms, Differential Evolutionary Algorithms, and Particle Swarm Optimization are much popularized amongst researchers across the world for reducing and optimizing dimensionality of satellite image features.

6. Acknowledgements

The authors wish to thank Director, Maharashtra Remote Sensing Applications Centre, Nagpur and Director, GHRCE for indeed support. We also owe our thanks to post graduate research scholar, Ms Pooja Mate for her inputs on few sections of the research paper. Last but not the least, we would like to express our sincere gratitude to all those who contributed directly or indirectly for this research article.

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