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Research Article

Remote Sensing Bid-Data Classification with Support Vector Machine

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Abstract: Remote sensing is the process of getting knowledge regarding some article or observable fact not including creation mental contact with the object. The data collected by deploying this method is termed as the remote sensing data. Data collected by this method may be either linear or non-liner in nature. For classification of linear statistics, we have used linear Support Vector Machine (LSVM) and for non-linear Support Vector Machine (NSVM) using different types of kernels.

Use of LSVM offers higher accuracy as compared with NSVM. In this paper, we have implemented concept of SVSA (Support Vector Selection and Adaption) for non-linear data with implementation, we have observed that this method offers higher accuracy as compared to selecting different kernel functions. We will use RACE data for training purpose, which will extent that the result of classification using this method which by passes the result of LSVM.

Keywords—Remote Sensing Data, Liner Support Vector Machine, Non-linear Support Vector Machine, Hyplerplan

1. Introduction

Remote sensing is assembly of data concerning Associate in Nursing object or development while not truly having physical contact with the thing. Nowadays, it is used naturally for atmospheric sensing techniques to discover and classify objects on Earth. Basically, it is of two types: passive remote sensing and active remote sensing. Passive sensors are used to detect radiation emitted or reflected from the body or surrounding areas. Film imaging, infrared, charge-coupled instruments, and radiometers are examples of passive remote sensors. Dynamic remote sensor is used for scanning objects by emitting energy. Examples are RADAR and LiDAR where we establish the locality, speed and way of an object by measuring the time delay between release and return.

In this paper, we have used SVM and its variations for Remote Sensing classification. Now-a-days more attentions have been given to SVM for classification of multispectral and hyper spectral remote sensing classification and SVM happens to be giving higher accuracy or at least equally well than other widely used pattern recognition techniques.

SVM is normally being recognized as Pattern recognition and machine learning with a non-parametric classifier. For straightly distinguishable examples SVM isolates the preparation tests into two classes inside a multi-dimensional component space by an ideal direct isolating hyper-plane .For straightly non-separable examples the info information is planned to high dimensional space where choosing the part work is the costly errand. Nonlinear SVM (NSVM) does the determination of piece capacities.

Though, SVM is designed for two class classification we may go for one-class classification. The One-Class Classification (OCC) problem is different from the conventional binary/multiclass classification problem in the sense that in OCC, the negative class is either not present or not properly sampled. The negative class as called as outlier data. With traditional SVM, OCC is problematic because it requires all classes to be labeled which is a difficult task as manually labeling data is time consuming and tedious.

The rest of the paper, arranged as follows: Section II gives insight into the related works; Section III describes support vector selection and adaptation. Section IV describes the Hybrid Model proposed. Section V discusses the computational complexities and Section VI, experimental results. Finally, paper is concluded with future scope in Section VII.

2. RELATED WORKS

Gómez-Chova et al. [1][2] have proposed a semi-supervised technique that joined unsupervised clustering, mean-map kernel, composite kernel, and SVM together to moderate the sample determination bias issue in remote sensing information classification. For remote sensing classification other semi-supervised leaning is also there such as graph based methods [3], semi-supervised SVM based cluster kernels[4], semi-supervised kernel based fuzzy C-means algorithm[5], Laplacian SVM [6], and weighted unlabeled sample SVM [7].

Although, the existing semi-supervised for learning methods are provide good performance by assigning unlabeled data into the training set, they have certain limitations such as many free parameters in this system and difficulty in finding iterations in TSVM[8]. Recently, Elkan and Noto have proposed a new Positive and Unlabeled Learning (PUL) algorithm that has good potential in one-class classification [9] as it does not require any labeling of negative data in the training set. This has shown promising results in document classification and Elkan [10] takes its usage with remote sensing and its evaluation proves its high accuracy classification criteria. Now, moving towards two class classification, problem arises when we have non-linearly separable classification. The use of NSVM is difficult as selection of kernel is a difficult task and it has high impact on learning capacity. Pal (2002) utilized five distinct kinds of portions (the straight part, the polynomial bit, the Radial Basis Function (RBF) bit, direct spline, and the sigmoid piece) which examinations the impact of bit decision on arrangement exactness utilizing multispectral information and proposed that the spiral premise and the direct splines perform similarly well and accomplish the most elevated precision for the dataset utilized in the analyses [11]. SVM is a moderately late improvement in the far-off detecting field.

Although, NSVM has high classification performance but it require high time for computation to map input to non linear kernel function. Thus, the ultimate task of NSVM lies on its part of selecting the kernel function. So, a new model called SVSA is designed to overcome the limitations of NLSVM which uses LSVM to obtain support vectors and select the reference vectors, with respect to training set data by using linear vector quantization. In SVSA, the computation time is less as compared to NSVM and we don’t have to do kernel selection. But, when SVSA is applied for linearly separable data it is being found that sometimes LSVM gives more accuracy than SVSA for certain data. So, to overcome this, a new mixture representation is explained Hybrid Support Vector Selection and Adaption (HSVSA) which uses the property of both LSVM and SVSA. HSVSA is designed give better accuracy for all type of data.

3. SUPPORT VECTOR SELECTION AND ADAPTATION

Support Vector Selection and Adaptation (SVSA) are a supervised nonlinear classifier that is applied for both linearly and nonlinearly separable data. The support vectors of LSVM, which are closest to the decision boundary, are used in the SVSA. SVSA basically consists of two stages: selection and adaptation of support vectors.

Algorithm of SVSA is:

Step1: Selection of support vectors is based on their contribution to overall classification accuracy called reference vectors.

Step2: They are using iteratively approach adapted and modified by with Learning Vector Quantization (LVQ) with respect to the training data.

These problems of NSVM and the computational power of SVSA are overcome by the kernel selection problem of NSVM. The aim of SVSA underlies the fact not to rise above the performance of NSVM, but to obtain extremely close classification performance to NSVM not including choosing any kernel function and kernel parameter at a lower computation time. It outperforms both LSVM and NSVM for linearly and nonlinearly separable data without the must for a kernel. SVSA's computational complexity is less than that of NSVM, i.e. actually the reason of using the SVSA inside the hybrid model.

4. THE HYBRID MODEL

A few examinations are finished with the LSVM, NSVM with various kinds of part capacities, and SVSA. As indicated by the outcomes acquired, it was seen that the NSVM, just as the SVSA, are relatively few productive classifiers for straightly detachable information contrasted with LSVM. A classifier that functions admirably with direct and nonlinearly divisible information is, thusly, a need. So a mixture model is proposed for consolidating the consequences of both LSVM and the SVSA.

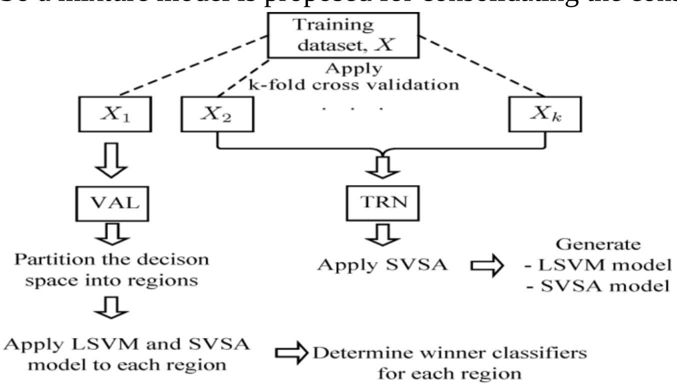


Fig. 1: The basic learning scheme for the proposed hybrid model for generation a hybrid classification with LSVM and the SVSA.

Every one of the datasets fills in as an approval set thus, and the excess information of the first preparing as another preparation dataset [11,14,16]. The Fig.1 above shows the essential learning plan of the proposed half and half model. According to proposed hybrid model:

Step1: The training data is taking randomly partitioned into sets.

Step 2: For each training single set, validation dataset is prepared to determine the winner classifier between LSVM and SVSA.

Step3: The remaining set is use to determine for separating hyper plane and the reference vectors as training dataset.

Step 4: For determining the winner classifier, the vertical distances from each data within the validation dataset to the optimum hyper plane are calculated and normalized.

Step 5: At last, the arrangement exactness for every technique is determined and the classifier with the most noteworthy characterization precision is resolved for every district, known as a victor classifier.

5. COMPUTATIONAL COMPLEXITIES

SVSA and HSVSA codes are created by utilizing both C and MATLAB contents while LIBSVM was executed both in C++ and Java programming language [13].

		Training	
LSVM	NSM	HSVSA	SVSA
$O(n^2)$	$O(n^3)$	$O(n^2 \log n)$	$O(n^2 \log n)$
		Testing	
O(n)	O(n)	O(nlogn)	Onlogn)

TABLE 1: COMPARISON OF TIME COMPLEXITY FOR TRAINING AND TEST DATASET.

The processing time could direct to incorrect decision as compiled Java and C++ are usually faster than MATLAB. Thus, in order to make fare deal we have two options:

i) All codes need to written in the same language.

ii) The computational complexity of the algorithms should mention.

For this reason, computational complexities are being given in the table above.

6. EXPERIMENTAL RESULTS

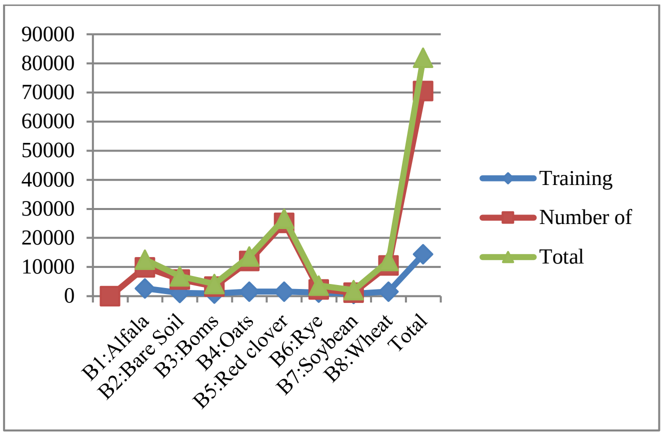
We have performed experiments for demonstrating our outcomes. Trials identified with multispectral far-off detecting picture were completed to pass judgment on the reasonableness of the proposed calculation. Here, Flight line B1 multispectral information taken over Tippecanoe Province, in June 1966 was utilized [11][12].

A. Flight line B1

The Flight line B1 is a multispectral dataset with 12 highlights. The entire scene is group with the proposed technique with 8 classes and comprising 9,496,220 pixels. The test and training data used in the experiment is tabulate in Table 2 below.

Class	Training	Number of Sample Test	Total
B1:Alfala	2684	9918	12602
B2:Bare Soil	1158	5734	6892
B3:Boms	891	3375	4266
B4:Oats	1530	12147	13686
B5:Red clover	1524	25174	26698
B6:Rye	1247	2385	3632
B7:Soybean	851	1230	2081
B8:Wheat	1520	10625	12145
Total	14414	70588	82002

TABLE 2. THE NUMBER OF TRAINING AND TEST SAMPLES FOR FLIGHTLINE B1

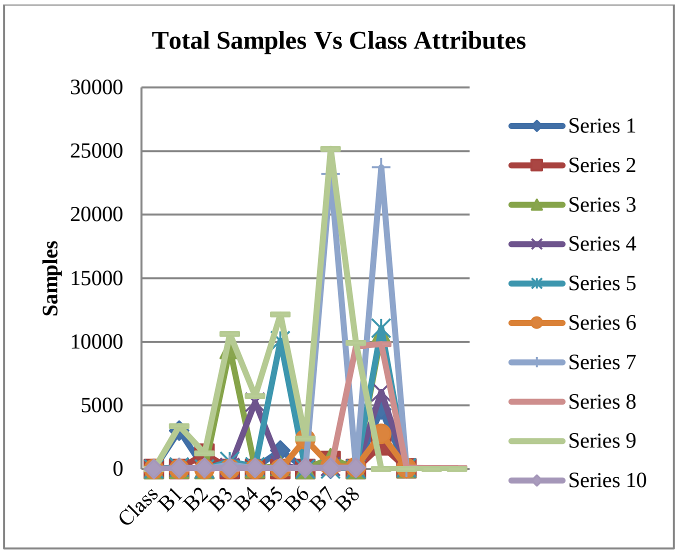


The classification performance of the HSVSA was contrasted with LSVM, NSVM with RBF, and polynomial part and SVSA. In this way, with the proposed mixture model, the presentation of the HSVSA achieves LSVM's classification performance which is the most elevated arrangement exactness. SVSA's classification performance is progress with the crossover model proposed in following Tables in this paper.

LSVM Classification

					Number of sample for each class					
Class	B1	B2	B3	B4	B5	B6	B7	B8	#Samples	UA
B1	3033	0	18	158	162	2	2	0	3375	89.9
B2	0	1222	1	0	0	0	7	0	1230	99.3
B3	89	1	9433	133	609	11	349	0	10625	88.8
B4	69	0	41	5263	190	3	60	108	5734	91.8
B5	1470	4	249	274	10094	1	55	0	12147	83.1
B6	0	1	0	5	0	2333	1	45	2385	97.8
B7	16	639	855	197	15	257	23195	0	25174	92.1
B8	0	1	0	35	0	162	52	9668	9918	97.5
	4677	1868	10597	6065	11070	2769	23721	9821	#sample	
	64.8	65.4	89.0	86.8	91.2	84.3	97.8	98.4	PA	
								88.7	Kappa	
								91.0	OQ	

TABLE 3. LSVM CLASSIFICATION SAMPLE VS CLASS ATTRIBUTE

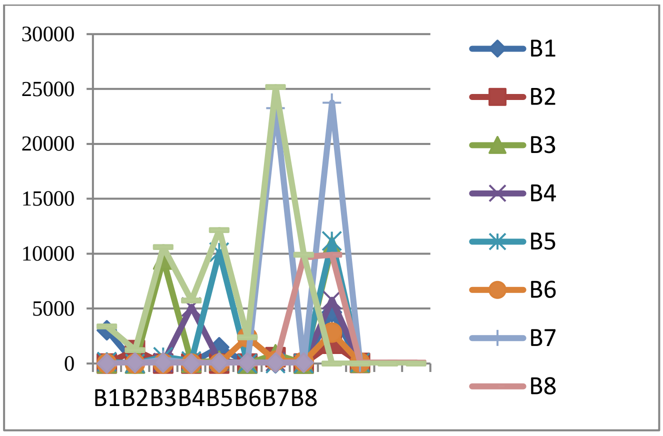


The HSVSA Classification

Number of samples for each class

Class	B1	B2	B3	B4	B5	B6	B7	B8	#Samples	UA
B1	3033	0	19	156	163	3	2	1	3375	89.8
B2	0	1222	1	0	0	0	7	0	1230	99.3
B3	89	3	9483	76	624	9	351	0	10625	89.3
B4	69	0	77	5151	222	4	63	156	5734	89.8
B5	1473	2	266	221	10132	1	51	4	12147	83.4
B6	0	1	0	4	0	2377	1	2	2385	99.7
B7	16	569	845	175	13	266	23264	27	25174	92.4
B8	0	2	0	23	0	161	24	9708	9918	99.7
	4650	1799	10691	5806	11154	2821	23769	9898	@sample	
	65.2	67.9	88.7	87.7	90.8	84.3	97.9	98.1	PA	
								89.0	Kappa	
								91.2	OQ	

TABLE 4.HSVM CLASSIFICATION SAMPLE FOR EACH CLASS TE

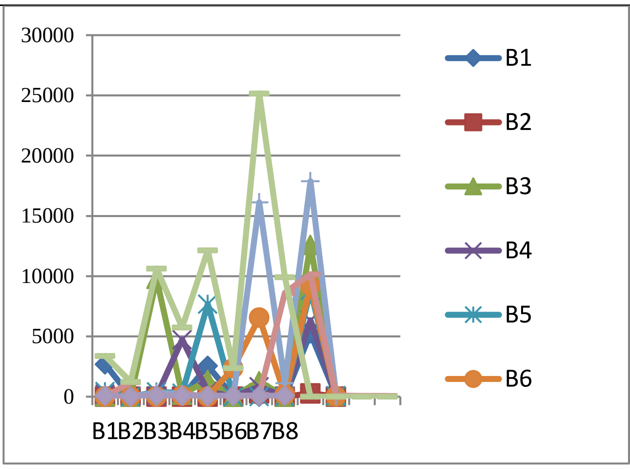


The SVSA Classification

Number of samples for each class

Class	B1	B2	B3	B4	B5	B6	B7	B8	#Samples	UA

B1	2693	0	30	220	422	8	0	2	3375	79.8
B2	0	9	1	0	0	0	2	1218	1230	0.7
B3	7	0	9772	67	410	20	341		10625	92.0
B4	9	0	174	4733	293	100	230	195	5734	82.5
B5	2555	4	1399	444	7693	6	42	4	12147	63.2
B6	0	0	0	18	0	2365	0	2	2385	99.2
B7	1	272	1274	841	8	6567	16126	134	25174	64.1
B8	0	0	0	18	0	162	1136	8602	9918	86.7
	5265	285	12600	6342	8826	9228	17877	10165	@sample	
	51.1	3.1	77.6	74.6	87.2	25.6	90.2	84.6	PA	
								68.1	Kappa	
								73.7	OQ	

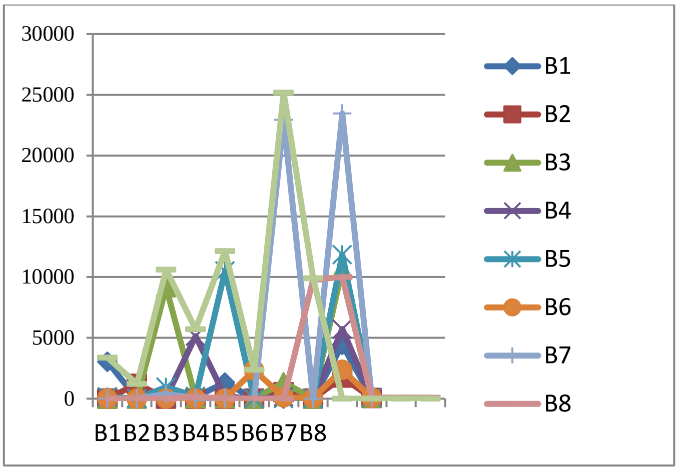


The NSVM Classification

Number of samples for each class

Class	B1	B2	B3	B4	B5	B6	B7	B8	#Samples	UA
B1	3049	0	16	130	178	2	0	0	3375	
B2	0	1217	1	0	0	0	12	0	1230	
B3	14	3	9165	86	960	9	388	0	10625	
B4	131	0	63	5132	185	2	54	167	5734	
B5	1329	6	73	189	10507	0	40	3	12147	
B6	0	0	0	2	0	2363	3	17	2385	
B7	21	527	1344	176	22	126	22948	10	25174	
B8	0	0	0	19	0	75	17	9807	9918	
	4445	1753	10662	5734	11852	2377	23462	10004	@sample	
	67.1	69.4	86.0	89.5	88.7	91.7	97.8	98.0	PA	
								88.6	Kappa	
								90.9	OQ	

TABLE 5: CLASSIFICATION RECORD FOR LSVM, NSVM AND SVSA WITH REMOTE SENSING DATA



CONCLUSIONS AND FUTURE SCOPE

In this paper, we have studied the performances of different linear and non-linear Support Vector Machine for remote sensing big-data data classification. We have observed that two-class or multiclass straightly and nonlinearly divisible information the mixture model takes the benefits of both LSVM and the SVSA productively. We have proposed a classifier HSVSA, in which missing vector is join to dataset for future training for classification. It is also observe that HSVSA outperforms LSVM for certain circumstances, LSVM performs better than SVSA. For one class classification, Positive and Unlabeled Learning (PUL) gives the greatest exactness.

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