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ANALYSIS OF SAR IMAGES TEXTURE USING RIM SUPPORT VECTOR MACHINES

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ABSTRACT

This paper studies the performance of RIM support vector machine in the analysis of SAR based images. Analysis of complex Synthetic Aperture Radar images remains an inspiring and unsolved problem in the field of research. This paper proposes an optimal methodology to classify SAR based images with the help of support vector machines embedded RIM. The methodology which is proposed in this study is to classify the SAR based images is based on machine learning algorithms. The proposed implicit SAR image classification methodology has got many application areas such as filtering, routing relevant images to suitable databases and search engines. Proposed methodology is described by high dimensional data in which every pixel of SAR image is treated as an attribute. All SAR images used under this study are collected from publicly available AXA EORC database. This paper describes a mathematical model for automatic SAR image classification which is implemented in R programming language. Many algorithms were proposed to classifying SAR images but one of the most promising methodology is RIM support vector machine. The results shown in this paper to classify SAR images are highly effective with accuracy of 94% without heuristic and greedy concepts.

Keywords: SVMs, SAR image, breast images and analysis methods.

1. INTRODUCTION

SAR images are basically obtained from satellite pictures which have got immense applications in the areas like ground water identification, glacier identification, volcanoes identification, land cover analysis and ice sea map analysis. Texture analysis and statistical methods are used to classify SAR images. SAR images also have immense applications in mapping of other planets and earth.

Effective classification of SAR image is very useful in remote sensing applications. Most of the classification algorithm is designed based on either supervised methods or unsupervised methods. PoISAR statistical image classification methods are based on supervised learning methods in which training is involved. All entropy SAR image classification algorithms are designed on the basis of unsupervised algorithm in which training is not involved [1]. Knowledge engineering forms theinitial phase of the automatic classification of SAR images into predefined classes. Designed classification procedures automatically classify the SAR images collected from publicly available EORC database.

A machine learning methodology is used to over come the problems associated with the absence of expertise knowledge. The job of designing training SAR image classification poses challenges like little training data, large input space, complex learning tasks, nose and computation efficiency. The methodology applied here makes use of the concept designed by Vapnik's idea of choosing optimal hyper plane that separates the data into classes [2].

This paper describes a novel machine learning methodology to the problem of training SAR image analysis from the sample image sequence. Designing the training model of SAR image classification, implementing and examining technical procedures for SAR image classification based on support vector machines.

2. LITERATURE SURVEY

L. Ferro *et al.* [3] proposed a classification algorithm that uses concepts derived from statistical characteristics and physical scattering attributes. Wishart *et al.* [4] developed a methodology which classifies SAR images based on Polari metric property. There are some classification methods that classify SAR images based on neural networks [5], polarimetric properties [6, 7, 8]. Genetic algorithms (GA) are one of the widely applied algorithm for SAR image classification with help of fitness function [9]. Immune clonal selection algorithm is designed to over come the drawbacks of GAs to some degree [9]. Support vector machine is useful to classify SAR image on the basis of texture attributes by ICSA [10].

Wavelets [11], co occurrence matrix and energy based methods are used for classifying land cover SAR images. Richard, Quegan and Oliver analyzed the difference between infrared sensor based images and synthetic aperture radar images [12]. Press *et al.* [13] proposed non symmetric method for classifying SAR images based on singular value decomposition theorem (SVD). Support vector machine is used to classify remote sensing images based on the machine learning algorithms [13]. SRM and ERM has been demonstrated high accuracy compared to the other empirical methods like neural networks.

Multistage auto regression model and probabilistic neural network models have been successively applied to classify SAR images [14]. Zheng and Yan [13] suggested one class SVM and two class SVM to categorize SAR images. Dekker proposed GLCM and GLRLM methods are used to classify the SAR images [12].

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3. TEXTURES ANALYSIS OF SYNTHETIC APERTURE RADAR IMAGE

Texture is one of the significant attribute used for classification SAR images. It is used to measure the intensity of the surface, regularity, coarseness and smoothness. Several types of texture surfaces are segmented using techniques like MRF algorithm [15], wavelet methods, STFT, co-occurrence matrix and principal component analysis. Gabor filter shows good performance compare to wavelets in segmenting the texture features of the SAR images. Textures plays very important role in the analysis and classification of regions of interest of the SAR image.

3.1. Gray-level co-occurrence matrix (GCM)

Texture features like regularity, smoothness and coarseness are analyzed by using an important statistical tool GCM [16]. It can represent gray levels of SAR images and intensity levels of digital image.

GCM is a two dimensional array and whose order is m by m. Each entry in this matrix is represented by pixel q(i,j) in which i and j represents gray level intensities of the SAR image. Two adjacent pixels are separated by an angle and distance d.

$$\begin{pmatrix} q(0,0) & q(0,1) & \dots & q(0,m-1) \\ q(1,0) & q(1,1) & \dots & q(1,m-1) \\ \dots & \dots & \dots & \dots \\ q(m-1,0) & q(m-1,1) & \dots & q(m-1,m-1) \end{pmatrix}$$

here m represents number of intensity levels of SAR image under the consideration. Gray level matrix is symmetric matrix which can be calculated using spatial frequencies of the SAR image.

This matrix is computed by conditional, joint probabilities distributions with angles 0, 45, 90 and 135 degrees.

$$=135;|y1-y2|=0,|x1-x2|=e(1)$$

$$=90;|y1-y2|=e,|x1-x2|=0(2)$$

$$=45;|y1-y2|=+d,|x1-x2|=-d(3)$$

$$=0;|y1-y2|=-d,|x1-x2|=0(4)$$

Here (x1,y1) is the first pixel and (x2,y2) is the second pixel.

Gray level matrix is used segment the texture information of the SAR image. The complete and detailed explanation of a local SAR image is calculated by Baye's theorem [17], occurrence probabilities and joint probabilities. For each texture feature present in SAR image, parameters like energy EN, correlation coefficient COC, sum average SA and contrast CN [18] are computed by following formulas.

$$EN=\sum_{i=0}^{m-1}\sum_{j=0}^{m-1} q^2(i,j)(5)$$

$$COV=\sum_{i=0}^{m-1}\sum_{j=0}^{m-1}\frac{(i-\mu_x)(j-\mu_y)q(i,j)}{\sigma_x\sigma_y}(6)$$

$$\mu_x=\sum_i i\sum_j q(i,j)(7)$$

$$\mu_y=\sum_j j\sum_i p(i,j)(8)$$

$$\sigma_x=\sum_j (j-\mu_y)^2\sum_i p(i,j)(9)$$

$$\sigma_y=\sum_i (i-\mu_x)^2 q(i,j)(10)$$

$$SV=\sum_{n=0}^{2m-2}\sum_{i=0}^{m-1}\sum_{k=0}^{m-1} mq(j,k)(11)$$

4. CLASSIFICATION OF SAR IMAGES WITH SVM

SAR image classification is processed through support vector machines in which data is optimally separated into maximum margin hyper plane given by the equation 12.

$$h(x)=\sum_{i=1}^{n}\alpha_i v(x,x_i)+k(12)$$

Where k is biased variable, v is the weight and k is indicating the different combinations of parameters. Figure-1 represents two dimensional example in which data is separated into separated classes with hyper plane. Figure-2 represents difference between small margin and large margin which separates data points into two different classes[19].

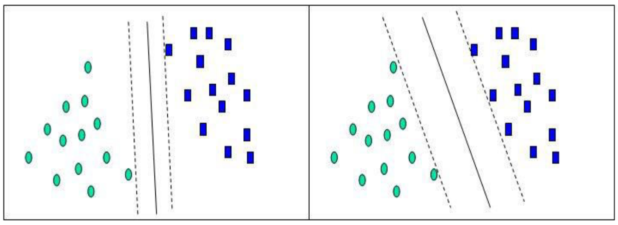

Figure-1. Two dimensional examples with support vectors.

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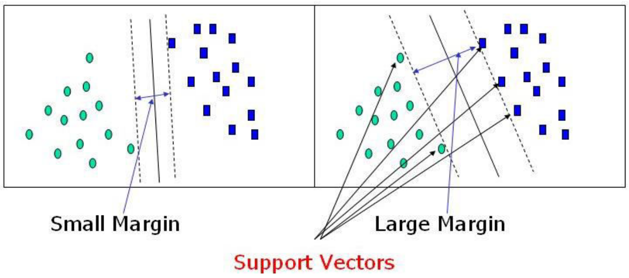

Figure-2. Support vectors with small margin and large margin

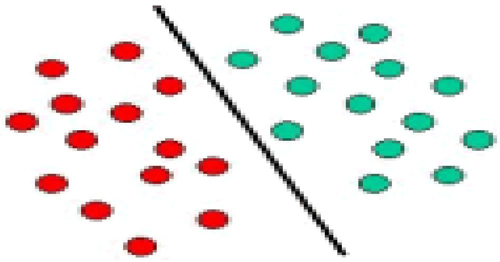

Figure-3. Linearly separable data with hyper plane.

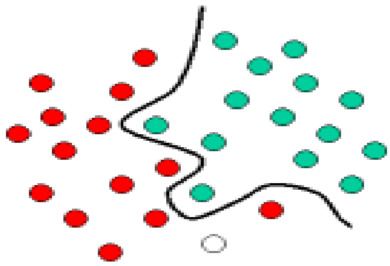

Figure-4. Linearly in seperable data with hyper plane.

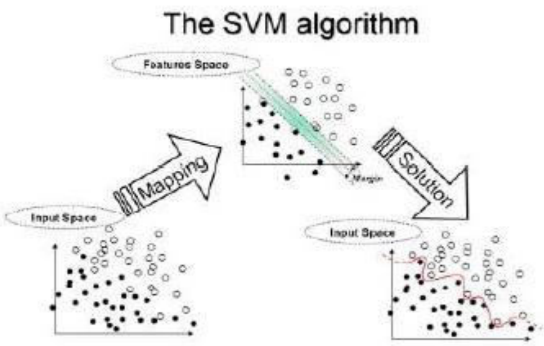

Figure-5. SVM algorithm approach.

Figure-1, Figure-2, Figure-3, Figure-4 and Figure-5 represents different cases in support vector machine algorithm classification.

The maximum hyper plane is constructed in feature space with non linear kernel transformation. The optimal margin between two hyper planes is calculated by the following formulas.

$$2/\|w\| \quad (13)$$

$$f(x) = \mathrm{sgn}\left\{ \sum_{xj} a_i * yj < xi.x > \right\} + b* \quad (14)$$

$$Kernel = \exp\left(\frac{\|xi \quad xj\|^2}{2 \quad ^2} \right) \quad (15)$$

SAR image classification comes under the category of non linear classification as they contain speckle. This leads to the calculation of the soft margins by Lagrangian multipliers. All the constraints are converted into equations by introducing slack variable. There are various type of SVMs such as binary classifier and multi class classifier for segmentation and classification SAR images. Number of classifiers are depending on the type of the problem formulated by considering different SAR images. We need n classifiers for n type problems and n(n-1)/2 classifiers in the case one against one method[20].

5. METHODOLOGY

The L-band and C-band SAR images are collected from the publicly available EORC database. In this paper two types of SAR images are considered in which is first one is related winter crops and second one is associated winter crops. Spring barely, spring rape, beats, potatoes and peace comes under spring crops and whereas crops like barley, wheat, winter rape and grass comes under winter crops which can be seen in Figure-6, Figure. 7[21, 22, 23, 24 and 25].

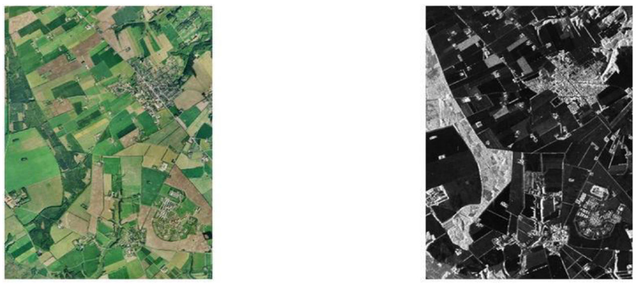

Figure-6. SAR image with optical and HH channel.

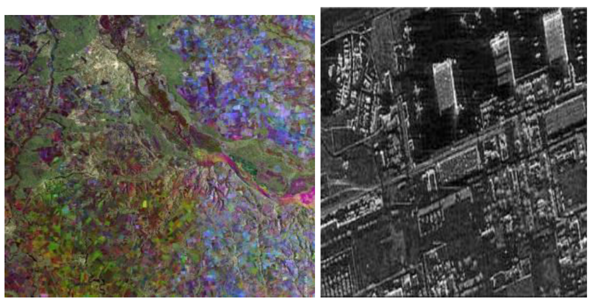

Figure-7. X-band SAR image.

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5.1 Proposed algorithm

a) Decompose and calculate the features of SAR image data with the help of GCC matrix and MCSM method as shown in Figure-1.

b) Form the feature vector space by features obtained in step1. Sequential backward extraction procedure used to remove the unnecessary features.

c) Normalization procedure is applied on the features obtained in step2, so that they will be under desire range.

d) Identify and analyze the learning samples of SAR image from step3.

e) Calculate kernel function, decision function and variables of support vector machines from the learning samples identified in step4.

f) Calculate accuracy of classification with help of testing samples as shown in Figure-9.

g) Trained classifier is used to analyze accuracy of eachSAR images which are obtained from EORC image database.

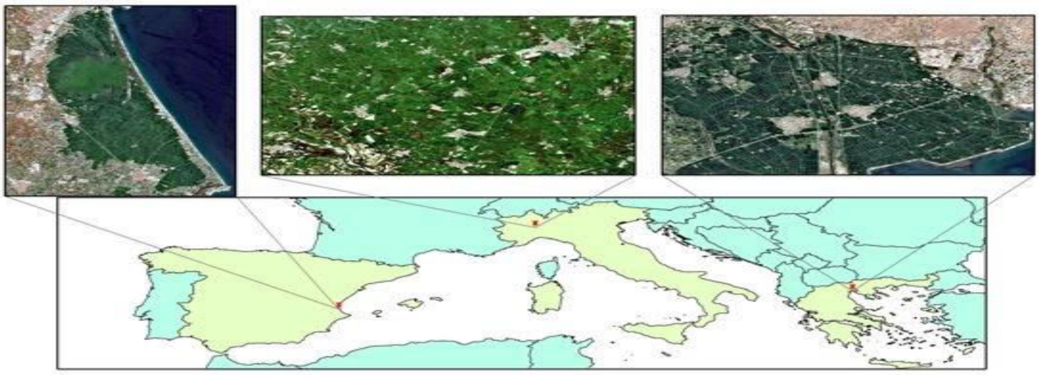

Figure-8. Result of GCM method on SAR image.

Figure-9. Example of trained SAR image.

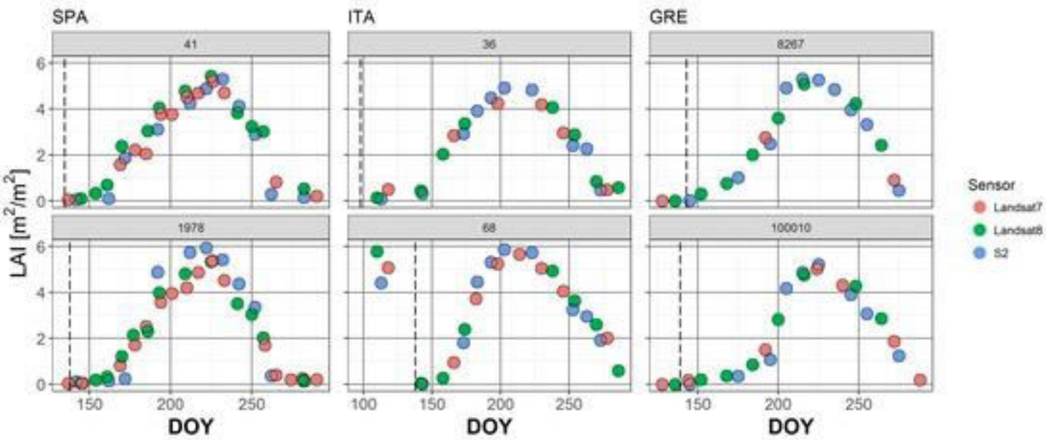

Figure-10. Accuracy sample images obtained in step7.

5.2 Results

The support vector machine classifier is constructed by choosing Radial basis function kernel to design optimal hyper plane. In this study multi classification problems are solved with the help of one-against-one algorithm. The parameters w and b are calculated with feature set of learning examples.

To obtain empirical analysis of the proposed classification methodology, we have chosen 1600 test cases of SAR images of 5 different groups. The accuracy of broad leave crop is 94%, small stem crop is 82%, bare field is 94%, forest field is 96% and building is 86% which are shown in Table-1. Total precision of the SAR image classification test data of different classes is 90.4%.test data of different classes. Double bounce characteristic of SAR images leads to misclassification of forest related into building related data. Prosper greenery property misclassified stem crops and broad leave crop. As a consequence of this support vector machines leads to relatively good accuracy results compare to other classification methodologies.

The bare field, buildings field and forest related SAR data are classified more accurately compare to other data. Texture feature played significant role in classifying bare field.

Table-1. Accuracy results of different SAR images CLASS 2.

	CLASS1					
TEST	**1**	**2**	**3**	**4**	**5**	**6**
1	1128	240	0	0	0	94%
2	432	932	0	0	1	82
3	0	0	1300	80	0	94%
4	0	0	25	1000	300	96%
5	10	15	0	89	1300	86%

Table-2. Accuracy results of different SAR image of CLASS2.

	CLASS2					
TEST	**1**	**2**	**3**	**4**	**5**	**6**
1	1228	340	0	0	0	94.2%
2	532	1034	0	0	1	82.1%
3	0	0	1400	180	0	93.45%
4	0	0	35	1101	300	94.83%
5	20	25	0	109	1300	86.24%

Here 1 represents data related to building
2 represents data related to forest
3 represents data related to bare field
4 represents data related to small stem crop
5 broad leaves crop and 6 represents accuracy

Table-3. Accuracy results of RIM SVM with different kernels.

D-SVM	**Building**	**Forest**	**Bare Field**	**Stem Crop**
	SVM	**0.73**	**0.45**	**0.654**
	SVM+RIM	**0.89**	**0.92**	**0.89**
D-SVM		Forest	Bare Field	Stem Crop
	SVM-1	0.415	0.538	0.5317
	SVM-2	0.335	0.3223	0.473
	RIM+SVM Linear	0.92	0.92	0.97
	RIM+SVM RBF	0.93	0.94	0.98
	RIM+SVM Poly	0.92	0.93	0.93
DC-SVM		Forest	Bare Field	Stem Crop
	SVM-1	0.5285	0.538	0.531
	RIM+SVM	0.92	0.91	0.92
V-SVM		Forest	Bare Field	Stem Crop
	SVM-1	0.527	0.5376	0.5337
	RIM+SVM	0.475	0.473	0.5872
C-SVM		Forest	Bare Field	Stem Crop
	SVM-1	0.93	0.86	0.91
	RIM+SVM	0.96	0.98	0.99

Results in the Table-1, Table-2 and Table-3 compares the classification of SAR images consisting of stem crop, bare field and forest. These results shows that RIM support vector machines shows significant improvement in classifying the images of different types. Volume scattering and double bounce are the major reasons for misclassification small stem crops SAR image data. The data related to buildings are classified correctly in most of the cases.

6. CONCLUSIONS

SVM method is general purpose method for classifying asymmetric and symmetric SAR based image data. Support vector machines used risk minimization principal to enhance the classification accuracy. Texture is the feature which played major role in the classification task. Results proved that SVM embedded with risk minimization principal is accurate and effective in the classification SAR images.

In this paper, we proposed support vector machines based on statistical learning theory used to segmentation of targets in SAR images. We systematically analyzed the performance of support vector machines on huge and variety number of SAR targets under different illumination conditions and backgrounds. The methods of performance that we used are segmentation precision, probability of recognition and wrong alarm rate.

This study explains the deep analysis of optimal selection of variables. This paper proves that algorithm performance depends on the appropriate selection of parameters. Hence, one can embark on optimal variable selection based on the SAR image metrics and also scene parameters.

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