Recent Research in Science and Technology 2011, 3(1): 105-113
ISSN: 2076-5061
www.recent-science.com

GEOPHYSICS

CLASSIFICATION OF FIELDS HAVING DIFFERENT SOIL MOISTURE CONTENT BY SVM TECHNIQUE USING BISTATIC SCATTEROMETER

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Abstract

In the present paper, the classification of four different fields having different soil moisture contents is done by Support vector machine (SVM) technique. The bistatic X-band scatterometer measurement were carried out for different soil moisture fields at HH- and VV- polarization. The scattering coefficient was found to increase with the soil moisture content, whereas, the nature of variation was observed opposite in HH- and VV- polarizations keeping soil roughness constant. The X-band bistatic scatterometer datasets are used for training and testing of the SVM. Our results show higher classification accuracy of SVM, even for the small size of the training data set. The present work confirms the classification ability of SVM technique to classify the fields having different soil moisture contents using bistatic scatterometer data.

Keywords: Support vector machine, soil moisture, surface roughness, scattering coefficient, polarization

Introduction

Water and energy fluxes are strongly dependent on soil moisture at the surface/atmosphere interface. Surface evaporation, infiltration and surface run off are not only influenced by soil moisture but also regulate the rate of water uptake by vegetation. The estimation of soil moisture is a significant factor for weather and climatic models and should be accounted for hydrology and vegetation monitoring [1]. Microwave measurement is least affected by cloud cover and varying surface solar illumination and can provide a method for monitoring the soil moisture at global and regional scales [2]. The microwave response of bare soil depends on wavelength, polarization, look angle of incidence wave, soil texture, soil temperature, soil surface roughness and soil moisture [3]. The sensitivity of microwave scattering to dielectric and geometric properties of natural surface makes microwave remote sensing as one of the most important technique for estimating soil moisture content. The dielectric properties of the soil are expressed primarily by the soil moisture content, while the geometric properties are related to the surface roughness.

The soil moisture content plays a significant role in understanding different ecological process as well the nature of global change. Soil moisture is a key factor in predicting, estimating and modeling large scale processes such as evaporation, transpiration, surface run off and ground water replenishment. The surplus or deficit of soil moisture affects the temporal and spatial dynamics of vegetation systems. Therefore, the understanding of temporal and spatial fluctuations of soil moisture is useful for prediction of plant growth determination by knowing the proper time for sowing, identifying agricultural area with increasing soil erosion or water logging and monitoring the dynamics soil processes acting on the surface (physical, chemical and biological). Soil moisture also proves to be a key factor in metrological modeling, weather predictions and flood monitoring [4]. Many models have been developed to understand the physics of the interaction between radar signal and surface and vegetation parameters [5, 6].

All the existing models, however, presented a variety of limitations. The region of the SPM and KA models enclose smooth surface only. Various natural surface conditions fall outside this region which makes the SPM and KA ineffective for such surfaces. However, the empirical and semi empirical models are more simplistic in their formulation as compared to the theoretical models and were applicable to a variety of different sites, they also had limited validity in region with high roughness and with soil moisture content beyond a certain range. This led to an over/under estimation of the soil moisture. Further, the models were developed based on the data acquired from bare soils and thus did not include the effects due to the backscattered from vegetation.

Computational model ANN is effective to non linear data sets and more accurate than the other

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conventional methods in soil moisture estimation [7]. Neural network classifiers are used in the remote sensing applications [8], but their performance are limited by certain factors [9]. A new classification technique known as support vector machines (SVM) is applied for the classification of remote sensing data [10, 11]. Thus, in this paper SVM classification technique is used for the classification of the different soil moisture fields. Bistatic X-band scatterometer data were used for the training and testing the SVM model. Results are much encouraging and confirm the utility of SVM model as a classifier of fields having different soil moisture content.

Description of support vector machine

SVM technique is an innovative kind of machine learning method introduced by Vapnik and co-workers [12]. This method is further enhanced by various investigators for different applications like classification, feature extraction, clustering, data reduction and regression in different disciplines. Our present analysis is based on the classification of multiclass data by employing SVM technique. This method builds a Hyperplane for separation of data into two classes in simple binary classification of linear separable training data vector $(x_1, x_2, x_3, \ldots\ldots, x_m)$ in n dimensional space. A class decision function associated with Hyperplane is weighted sum of training data set and bias are symbolized [12,13,14] as

$$y(x) = w^T\Phi(x) + b \quad (1)$$

where w and b are weight vector normal to Hyperplane and bias value respectively. New test data is assigned to a class according to sign of decision function as:

test data belongs to class-1 if

$$w^T\Phi(x) + b > 0 \quad (2)$$

test data belongs to class -2 if

$$w^T\Phi(x) + b < 0 \quad (3)$$

and

$$w^T\Phi(x) + b = 0 \quad (4)$$

corresponds to the decision boundary. Weight vector and bias value for optimal Hyperplane SVM are obtained by maximizing the distance between the closest training point and Hyperplane. This is done by maximizing the margin defined as $M = \frac{2}{|w|}$, same as minimization of

$$\frac{\|w^2\|}{2} \quad (5)$$

under the constraint

$$y_i(w^T x_i + b) \geq 1 \quad (6)$$

A number of mathematical algorithms exist for finding weight and bias values under the condition (5) and (6). One of the most widely method used in SVM is Quadratic Optimization problem. Its solution involves construction of dual problem with introduction of Lagrange multiplier α_i as follows:

$$\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum \sum \alpha_i\alpha_j y_i y_j x_i x_j \quad (7)$$

Maximization was done under the conditions

$\sum\alpha_i y_i = 0$ and $\alpha_i \geq 0$

for all value of $i = 1, 2, \ldots\ldots, N$. After solving optimization problem, the values of weight and bias are obtained as

$$w = \sum\alpha_i y_i x_i \quad (8)$$

and $b = y_k - w^T x_k$ (9)

where x_i is support vector for each nonzero value of α_i. Hence, the classification function for a test data point x is inner product of support vector and test data point as fallows

$$y(x) = \sum\alpha_i y_i x_i^T x + b \quad (10)$$

For binary classification of nonlinear training data points, SVM maps n-dimensional data vector x into a d-dimensional feature space ($d > n$) with help of a mapping function $\Phi(x)$. Mapping function provides a Hyperplane separating the classes in high dimensional feature space. Hyperplane maximizes the margin between classes using standard Quadratic Programming (QP) optimization technique. Closest data point to the Hyperplane are used to measure the margin and named as support vector. In dual formulation of quadratic optimization problem instead of using dot product of training data points in high dimensional feature space, kernel trick is used. Kernel function defines the inner product of training data points in high dimensional feature space and defined as

$$k(x_i, x_j) = \Phi^T(x_i)\Phi^T(x_j).$$

It reduces the mathematical computational complexity in higher dimensional feature space. Commonly used kernel functions are linear, polynomial, radial Gaussian and sigmoid are defined as follows:

$$k(x_i, x_j) = x_i \cdot x_j$$
- Linear kernel function

$$k(x_i, x_j) = (x_i \cdot x_j + c)^d \quad \text{for} \quad d \geq 2 \quad \text{and} \quad c > 0$$
- Polynomial kernel function

$$k(x_i, x_j) = e^{-\|x_i - x_j\|^2 / 2\sigma^2} \quad \text{for } \sigma > 0$$
- Radial Gaussian kernel function

$$k(x_i, x_j) = \tanh(\beta_0 x_i^T x_j + \beta_1)$$
- Sigmoid kernel function

Using kernel trick dual problem mentioned in (7) is expressed as maximization of

$$\sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum \sum \alpha_i \alpha_j y_i y_j k(x_i, x_j) \quad (11)$$

Under the same condition as $\sum \alpha_i y_i = 0$ and $\alpha_i \geq 0$. Optimization technique for finding out α_i, for $i = 1, 2, 3, \ldots\ldots, N$ remains the same. Now, the new classification function using kernel function is defined as follows:

$$y(x) = \sum \alpha_i y_i k(x_i, x_j) + b \quad (12)$$

For using SVM as multi classification problem, the entire data set is divided into several binary classes and model is trained. Further, test data points are classified with these binary class trained model and final decision about class of data point is taken on the basis of majority voting of class.

Present analysis based on SVM is implemented in statistical computing language R using e1071 package [15-16]. SVM model was optimized by different kernel function available in package with their tuning parameters. The scattering coefficient measured at different soil moisture content in the angular range of 20^0 to 70^0 for HH- and VV- polarization are taken as input for SVM model. The output of the SVM model is in the form of confusion matrix and decision values. Confusion matrix is a visualization tool for the classification commonly used in supervised learning. Rows of the matrix represent the instances in a predicted class, and columns correspond to the instances in an actual class. Decision value for each instance represents the output calculated by decision function given in equation (12). Decision value decides the assignment of instance to a particular class.

Result

Test bed of dimensions 3m x 3m of bare soil was prepared to carry out bistatic measurements at X-band (9.5 GHz) in the Department of Applied Physics, I.T., B.H.U, Varanasi. The bistatic scatterometer system was designed for the classification of fields having different soil moisture content at HH- and VV-polarizations in the angular range of incidence angle 20^0 to 70^0. The calibration of the system was checked during the experiment to ensure the system integrity. The surface roughness was taken smooth and constant during entire observations to study the microwave response of soil moisture content only. The antennas were placed in far field region from the centre of the target to minimize the near field interactions. Figures 1 and 2 depict the angular variation of scattering coefficient at different soil moisture contents for HH- and VV- polarizations respectively. The scattering coefficient was found to increase with soil moisture content, whereas, the nature of angular variation of scattering coefficient was observed opposite in the HH- and VV- polarization keeping soil surface roughness constant during entire observation. The effect of soil moisture content is more distinctly observed at low incidence angle in both the polarization.

Fig. 1 Angular variation of $\sigma^0(dB)$ at different soil moisture content for HH- Polarization.

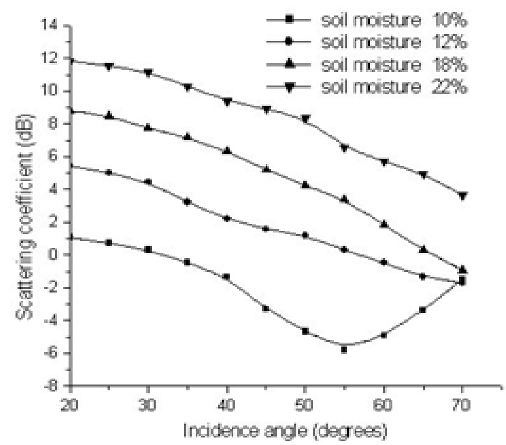
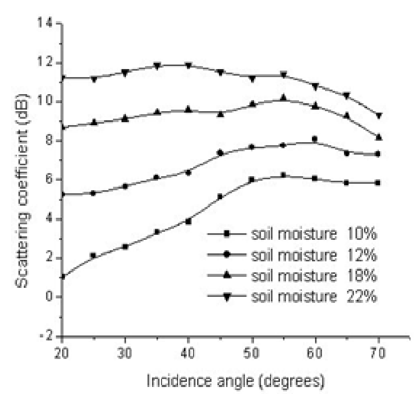


Fig. 2 Angular variation of $\sigma^0(dB)$ at different soil moisture content for VV- Polarization



Bistatic scatterometer data sets obtained during observation were used to train and test the classification ability of the SVM model. In the beginning, SVM network was trained with commonly used kernels like linear, polynomial, Gaussian radial basis, hyperbolic tangent and Laplacian to obtain the best kernel function which can optimized SVM model for classification task. Among different types of available kernel function, Gaussian radial basis provides an optimized SVM model for classification of soil moisture both in training and testing stage. Data sets consist of four soil moisture content as 10%, 12%, 18% and 22% having constant soil surface roughness for HH- and VV- polarization. Soil moisture content 10%, 12%, 18% and 22% are classified as class a, b, c and d respectively in our present analysis.

Table 1. SVM network output for Test data set in the form of decision value at HH-polarization

Test data set decision value						
S. No.	a/b	a/c	a/d	b/c	b/d	c/d
1	1.1321656	1.38586557	1.2105384	0.58327542	0.522673811	0.09848584
2	0.1427275	1.37675805	1.22690981	1.23117681	1.209085893	0.83305533
3	-0.3954703	0.93392797	0.98232808	1.11056451	1.284061137	1.16554536
4	-0.1715596	1.14955239	1.10550482	1.19522718	1.275221828	1.03056885
5	-1.0033756	-0.01622569	0.3594499	0.44869216	0.995917329	1.42821983
6	-1.1605923	-0.52985969	-0.04478561	-0.06548899	0.643887886	1.34237637
7	-1.1597616	-1.07956814	-0.59377778	-0.80604689	-0.007430271	0.85958875
8	-1.1283061	-1.15410663	-0.69451964	-0.94430944	-0.154307953	0.70149161
9	-1.047061	-1.24281339	-0.85367463	-1.16243815	-0.414838715	0.37001752
10	-0.5843011	-1.01973344	-1.04649015	-1.41077479	-1.052909882	-1.04422698
11	-0.5816705	-1.01656146	-1.04557769	-1.40944761	-1.054082716	-1.05081087
12	-0.7788974	-1.20312551	-1.05665947	-1.43269143	-0.894761514	-0.50989096

Table 2. SVM network output for Test data set in the form of decision value at VV-polarization

Test data set decision value						
S. No	a/b	a/c	a/d	b/c	b/d	c/d
1	0.005976035	0.58528261	0.8259114	0.99999998	1.07365026	1.0435193
2	0.930086456	1.15959195	1.2309742	0.81056221	0.80381292	0.7854896
3	1.029496697	1.09276077	1.1103779	0.59612752	0.57787603	0.6030483
4	-0.968654761	-0.72324463	-0.5460997	0.08283397	0.27590776	0.6401161
5	-0.40009063	0.17291596	0.4408573	0.85002063	0.96620206	1.017432
6	0.258373466	0.79649923	1.0057506	1.02524396	1.07537758	1.0224174
7	-0.827037897	-1.06881334	-1.1892404	-0.87764255	-0.72213436	-0.2274296
8	-1.004278333	-0.89040683	-0.7734234	-0.18084604	0.01867967	0.4603993
9	-0.484273409	0.07368548	0.3424462	0.79688053	0.92282646	0.9998217
10	-0.344353267	-0.69257939	-1.0756135	-1.03884192	-1.04206135	-0.962455
11	-0.658757256	-0.99026654	-1.2207838	-1.04729711	-0.94183057	-0.5455908
12	-1.001047285	-0.96498149	-0.8888169	-0.33459049	-0.13573688	0.3413391

For each class of soil moisture, there are 11 input data in HH- and VV- polarization. Eight data from each class at incidence angles 20^0, $25^{0,}$ 35^0, $40^{0,}$ 50^0, 55^0 65^0 & 70^0 were used in training of SVM model. Last three data sets at the incidence angles 30^0, 45^0 & 60^0 were used as test set for both the polarizations. Raw data set is mean centered before employing them as input of SVM model both in training and test phase for both polarizations.

Table 3. Confusion matrix for Test data set at HH- polarization

Predicted Class	True Class: Class- a Surface soil moisture (10 %)	Class -b Surface soil moisture (12 %)	Class -c Surface soil moisture (18 %)	Class -d Surface soil moisture (22 %)	Classification Rate (%)
Class -a Surface soil moisture (10 %)	2	0	0	0	83%
Class -b Surface soil moisture (12 %)	1	2	0	0	
Class -c Surface soil moisture (18 %)	0	1	3	0	
Class -d Surface soil moisture (22 %)	0	0	0	3	

Table 4. Confusion matrix for Test data set for VV- polarization

Predicted Class	True Class: Class- a Surface soil moisture (10 %)	Class -b Surface soil moisture (12 %)	Class -c Surface soil moisture (18%)	Class -d Surface soil moisture (22 %)	Classification Rate (%)
Class -a Surface soil moisture (10 %)	3	1	0	0	67%
Class -b Surface soil moisture (12 %)	0	2	1	0	
Class -c Surface soil moisture (12 %)	0	0	1	1	
Class -d Surface soil moisture (22 %)	0	0	1	2	

In HH polarization, the SVM model was optimized by Gaussian radial kernel function with training parameter $\gamma = 0.5$ for all the four classes of soil surface moisture. Output of SVM model in the form of decision value is summarized in Table 1. Model results 83% correct classification rate for test data set whose confusion matrix is given in Table 3. Excluding class c (soil moisture 18%) and using the same kernel function, the decision value output obtained is summarized in Table 5. In this case, 89 % correct classification rate is obtained whose confusion matrix is given in Table 9. The decision value output of model excluding class b (soil surface moisture 12%) is given in Table 6. Now, the SVM model attains 100% correct classification rate for test data set whose confusion matrix is specified in Table 10. The improvement in correct classification rate by excluding class b is logical i.e. due to very close values of two soil moisture classes a (10%) and b (12%).

Table 5. SVM network output for Test data set in the form of decision value for HH-polarization

S. No.	a/b	a/c	b/c
1	1.4008345	1.2619822	0.2875485
2	1.3513058	1.25454	1.0066156
3	0.939294	0.9804058	1.2536642
4	-0.9388082	-0.5966154	0.7852481
5	-1.0240687	-0.6951071	0.6480209
6	-1.1430356	-0.851944	0.3666831
7	-1.1124666	-1.0654502	-0.8222752
8	-1.1103667	-1.0647616	-0.8280334
9	-1.2140711	-1.0619544	-0.3670781

Table 6. SVM network output for Test data set in the form of decision value for HH-polarization

Training data set decision value			
S. No.	a/b	a/c	b/c
1	1.0541861	1.26008392	0.6859396
2	0.1255372	1.25466501	1.3120464
3	-0.3521086	0.98094598	1.3308406
4	-0.1527859	1.11578061	1.3450924
5	-0.9152291	0.33765939	0.9958261
6	-1.0846996	-0.06327352	0.6472242
7	-0.6934214	-1.06039057	-1.0738255
8	-0.6909937	-1.05964684	-1.0757052
9	-0.8648102	-1.06060192	-0.8746815

Table 7. SVM network output for Test data set in the form of decision value for VV-polarization

Test data set decision value			
S. No	a/b	a/c	b/c
1	-0.01574208	0.8334519	1.0639641
2	0.88143714	1.2259642	0.8081676
3	1.00835503	1.1092524	0.5813789
4	-0.96009659	-0.4865823	0.2659488
5	-0.39849539	0.4659261	0.951535
6	0.22235556	1.0057609	1.0697059
7	-0.43020686	-1.0737922	-1.0545454
8	-0.73596595	-1.1981942	-0.9396027
9	-1.0141257	-0.8294322	-0.1385393

Table 8. SVM network output for Test data set in the form of decision value for VV-polarization

Test data set decision value			
S. No	a/b	a/c	b/c
1	0.5997127	0.8339985	1.0202841
2	1.1576511	1.2272484	0.820058
3	1.0929902	1.1105127	0.6485185
4	-1.0603725	-1.1547617	-0.2757072
5	-0.8429687	-0.7089669	0.3760987
6	0.1085964	0.3750749	0.9459508
7	-0.7285183	-1.0764819	-0.9609572
8	-1.002913	-1.2045897	-0.5686123
9	-0.9225045	-0.8270366	0.2600899

Table 9. Confusion matrix for Test data for HH- polarization

Predicted Class	True Class			Classification Rate (%)
	Class -a Surface soil moisture (10%)	Class -b Surface soil moisture (12 %)	Class -d Surface soil moisture (22 %)	
Class -a Surface soil moisture (10 %)	2	0	0	89%
Class -b Surface soil moisture (12 %)	1	3	0	
Class –d Surface soil moisture (22 %)	0	0	3	

Table 10. Confusion matrix for Test data for HH- polarization

Predicted Class	True Class			Classification Rate (%)
	Class -a Surface soil moisture (10 %)	Class -c Surface soil moisture (18%)	Class -d Surface soil moisture (22 %)	
Class -a Surface soil moisture (10 %)	3	0	0	100%
Class -c Surface soil moisture (18 %)	0	3	0	
Class -d Surface soil moisture (22 %)	0	0	3	

Table 11. Confusion matrix for Test data for VV- polarization

Predicted Class	True Class			Classification Rate (%)
	Class -a Surface soil moisture (10 %)	Class -b Surface soil moisture (12 %)	Class -d Surface soil moisture (22 %)	
Class -a Surface soil moisture (10 %)	2	1	0	78%
Class -b Surface soil moisture (12 %)	1	2	0	
Class -d Surface soil moisture (22 %)	0	0	3	

Table 12. Confusion matrix for Test data for VV- polarization

Predicted Class	True Class			Classification Rate (%)
	Class -a Surface soil moisture (10 %)	Class -c Surface soil moisture (18%)	Class -d Surface soil moisture (22 %)	
Class -a Surface soil moisture (10 %)	3	1	0	67%
Class -c Surface soil moisture (18 %)	0	1	1	
Class -d Surface soil moisture (22 %)	0	1	2	

In VV polarization, the SVM model was optimized by Gaussian radial kernel function with training parameter $\gamma = 0.5$ for all the four classes of soil moisture content. The output of model is summarized in form of decision value in Table 2. The correct classification rate obtained was only 67% for test data set whose confusion matrix is shown in Table 4. The decision value output obtained by excluding class "c" (soil moisture 18 %) is summarized in Table 7. In this case, the model improves and 78 % classification rate was obtained for the test data whose confusion matrix is shown in Table 11. Similarly, the SVM model was trained excluding class "b" (soil moisture 12%) whose decision value output is shown Table 8. The correct classification rate for test data set reduces to only 67% whose confusion matrix is shown in Table 12.

Conclusion

Present study describes the results from an optimized SVM network used for classification of soil surface moisture. An optimized SVM model was obtained using radial Gaussian kernel function with training parameter $\gamma = 0.5$. The developed SVM model predicts the soil moisture class with high accuracy at HH- polarization. The present work confirms the ability of SVM model as a useful tool for the classification of the different classes of soil moisture contents using bistatic scatterometer data. The results suggest that the bistatic scatterometer measurement for the classification /estimation of soil moisture content is superior at HH-polarization in comparison to VV-polarization.

Acknowledgement

Authors are thankful to Prof. K. K. Shukla of the Department of Computer Science, I.T., B.H.U., Varanasi, for useful guidelines during the experiment and analysis.

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