Retrieval of Bare-surface Soil Moisture from Simulated Brightness Temperature Using Least Squares Support Vector Machines Technique

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Abstract— Soil moisture is an important parameter for hydrological and climatic investigations. It also plays a critical role in the prediction of erosion, flood or drought. In this paper, we explore the use of the support vector machine technique for modeling soil moisture inversion. LS-SVM is improved by the standard SVM and has more attractive properties. Experimental tests are carried by using the different set of training and test data. The methodologies have been applied to two sets of data to retrieve soil moisture and obtained the root mean squared error (RMSE) and the determination coefficient (R^2). The emissivity model (Q/H model) is applied to acquire the brightness temperature. The frequencies of interest include 1.4 GHz (L-band) of the soil moisture and ocean salinity (SMOS) sensor at two incidence angles and 6.9 GHz (C-band) of the advanced microwave scanning radiometer (AMSR) viewing angle of 55 deg. The effectiveness is assessed by considering various combinations of the input features. This study demonstrates the great potential of LS-SVM in the retrial of soil moisture from passive microwave remotely sensed data.

1. INTRODUCTION

The soil moisture of the bare-surface soil plays a key role of seasonal climate evolution and prediction because that it is a critical parameter in the mass and energy transfer between the soil and atmosphere [1]. The retrieval of surface soil moisture based on land surface hydrology models is of great important in myriad applications, including agriculture, water resource management to numerical weather foresting, climate change, and monitoring events (e.g., floods and droughts) [2].

Passive microwave remote sensing is a viable method in the research on land surface parameters. Recently, much effort has been devoted to effective approaches to estimate soil moisture and other surface parameters. Generally, there are two types of approaches to be used: physical modeling and semiempirical [3] in recent years. The traditional theories: the small perturbation (SPM), Kirchhoff approximation (KA). Moreover, the integral equation model (IEM) has demonstrated a much wider applicable scope for surface roughness conditions [4]. The empirically adopted IEM (EA-IEM) fit a wide range of soil dielectric constants, incidence angles [5]. For the semiempirical models, the Q/H model presented by Wang and Choudhury [6, 7], is a function of the surface roughness and dielectric properties and widely used in the remote sensing community. Now, many studies and methods have been undertaken in radar sensing research to retrieve the soil moisture and surface roughness [8–11]. Combined experimental or a model-based data, several papers applied the artificial neural network (ANN) and support vector regression. LS-SVM were introduced [12, 13] as reformulations to standard SVM which simplify the training process of SVM in a great extent by replacing the inequality constraints with equality ones. LS-SVM has been applied to forecasting in many areas of engineering.

Therefore, in this study, the goal is to approach the soil moisture of the inversion problem by using LS-SVM combined with Q/H model, and manage to enhance the accuracy of the retrieval process.

2. MICROWAVE SOIL MOISTURE RETRIEVAL APPROACH

2.1. Surface Roughness Model

In many studies, the Q/H model was the most commonly used to describe roughness surface radiation [6, 7]. The measurements of electromagnetic radiation emitted or reflected by soil surface, which can monitor the soil moisture. The expression of surface of the brightness temperature is given below

$$T_B = e \cdot T_S \tag{1}$$

where T_B is the brightness temperature, T_S is the soil surface temperature and e is the soil emission. This equation descripts the fact that both surface temperature and emission decide soil surface brightness temperature. Besides, soil brightness temperatures have linear relation with emission at the fixed soil surface temperature according to Eq. (1). e is decided by the characteristic of target object and related to the reflectivity r by reciprocity: $e = 1 - r$. Relate to smooth surface reflectivity, rough surface reflectivity can expressed as

$$r_{sp} = [(1 - Q)r_{op} + Qr_{oq}] \exp(-h) \tag{2}$$

where, r_{sp} is the rough surface reflectivity, the subscript p and q denote either V or H polarization. For a homogeneous soil with a smooth surface, the reflectivity at V and H polarization r_{ov} and r_{oh} are given by the Fresnel expression

$$r_{oh} = \left|\left(\cos\theta - \sqrt{\varepsilon_r - \sin^2\theta}\right)\Big/\left(\cos\theta + \sqrt{\varepsilon_r - \sin^2\theta}\right)\right|^2 \tag{3}$$

$$r_{ov} = \left|\left(\varepsilon_r\cos\theta - \sqrt{\varepsilon_r - \sin^2\theta}\right)\Big/\left(\varepsilon_r\cos\theta + \sqrt{\varepsilon_r - \sin^2\theta}\right)\right|^2 \tag{4}$$

where θ is the incidence angle and ε_r is the complex dielectric constant of the soil that depends primarily on the soil moisture content. In Q/H model, Q is a mixing parameter between polarizations V and H, and can be discarded sometimes. In theorythe parameter $h = (4\pi\sigma\cos\theta/\lambda)^2$ is used for surface roughness correction.

2.2. Least Square Support Machines Regression

LS-SVM are reformulations, the result in a set of linear equations instead of a quadratic programming problem for SVM. The x_i and y_i are the input and the output of the ith example, l presents the number of samples, consider a given training set: $\{(x_i, y_i)|x_i \in R^l, y_i \in R\}_{i=1,2,\ldots,l}$. The goal of the support vector method is to construct a regression of the following form

$$y = \omega^T\phi(x) + b \tag{5}$$

where $\phi(\cdot)$ is the nonlinear map mapping the input space to a usually high dimensional feature space, $\omega \in R^l$ is coefficient vector and $b \in R$ is bias term. These unknown parameters ω and b can be obtained [12, 13]

$$\min J(\omega,\xi) = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{l}\xi_i^2 \quad s.t. \quad y_i\left[\omega^T\phi(x) + b\right] = 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, 2, \ldots, l \tag{6}$$

The Lagrange corresponding to Eq. (6) can be defined as follows:

$$L(\omega,\xi,\alpha) = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{l}\xi_i^2 - \sum_{i=1}^{l}\alpha_i\left(\omega^T\phi(x_i) + b + \xi_i - y_i\right) \tag{7}$$

where α_i $(i = 1, 2, \ldots, N)$ are the Lagrange multipliers. The value of ω and ξ are obtained from the solution, and the Kuhn-Tucker conditions can be expressed by

$$\begin{bmatrix} 0 & \vec{1}^T \\ \vec{1} & z^Tz + \gamma^{-1}I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{8}$$

where I is the identity matrix, $z = [\phi(x_1), \ldots, \phi(x_l)]$; $y = [y_1, \ldots, y_l]^T$; $\vec{1} = [1, \ldots, 1]^T$; $\alpha = [\alpha_1, \ldots, \alpha_l]^T$.

The solution of αa nd b can be obtained by solving Eq. (8) and substitute to Eq. (5). According to the Mercer rule, the Kernel function $K(x_i, y_j) = \phi(x_i)^T\phi(y_j)$ Eq. (5) is presented as:

$$y(x) = \sum_{i=1}^{l}\alpha_iK(x_i, x) + b \tag{9}$$

3. DATA SET AND DESIGN OF EXPERIMENTS

In order to evaluate and characterize the effect of roughness on surface emission. Meanwhile, SM is sensitive to low-frequency ban at bare or low vegetated soils. We generated a simulated surface emission data based for two specific frequencies 1.4 GHz of the SMOS sensor and 6.9 GHz of the AMSR, respectively. Some initial specific parameters are related in the process of SM simulation, e.g., the soil surface temperature, the structure of the surface soil texture, soil bulk density (p_s), surface roughness etc.. According to the some reference, we designed the study area SM simulation input data sets, which were listed in Table 1.

The training of the LS-SVM data have been simulated in terms of the soil surface emissivity dual-polarization from Eq. (1). We set the soil moisture content (MV) from 2%–42%, and σ in the range of 0.1–1.6 cm. For simulated data sets, we converted into soil dielectric constant model [18], and generated MV and brightness temperature more than 900 samples. The inputs are the brightness temperature, the outputs is the MV as well. Considering the input parameters affect the estimation, various combinations are taken in account, the following design of experiments:

(1) three 1-D modes: a) two L-band 1-D modes: emissivity polarization H and V at 1.4 GHz and incidence angles 20 and 40 deg respectively; b) one C-band 1-D mode: emissivity dual-polarization at 6.9 GHz at an angle of 55 deg.

(2) one L-band 2-D mode: combine two angles of incidence that correspond to one L-band 2-D mode, i.e., dual-polarization at 1.4 GHz at angles of 20 and 40 deg.

(3) three integrated C- and L-band modes: at C-band combined with the front two steps to become integrated C- and L-band multiple dimensional emissivity modes.

Table 1: Data sets of soil moisture simulated.

Parameters	Temperature	Sand (g/g)	Clay (g/g)	p_s (g/cm^3)	Frequency	Incidence angle
value	23°	42%	18%	1.4	1.4, 6.9 GHz	20, 40, 55 deg

Table 2: The R^2 and RMSE of SM by the LS-SVM and BPNN method.

EXPERIMENTS		LS-SVM		BPNN	
		R^2	RMSE (%)	R^2	RMSE(%)
L-band 1-D mode	1.4 GHz/20 deg	1.0	0.0016	0.997172	0.8838
	1.4 GHz/40 deg	1.0	0.0002	0.999435	0.5780
AMSR mode	6.9 GHz/55 deg	0.990461	1.595	0.98775	1.8105
L-band 2-D mode	1.4 GHz/20 + 40 deg	1.0	0.0023	0.997296	0.8489
combined 6.9 GHz and L-band 1-D mode	6.9 GHz/55 deg, 1.4 GHz/20 deg	0.999548	0.3696	0.997590	0.9651
	6.9 GHz/55 deg, 1.4 GHz/40 deg	0.999961	0.1216	0.998976	0.6049
3-D mode	6.9 GHz/55 deg, 1.4 GHz/20,40 deg	0.999968	0.11	0.998793	0.6414

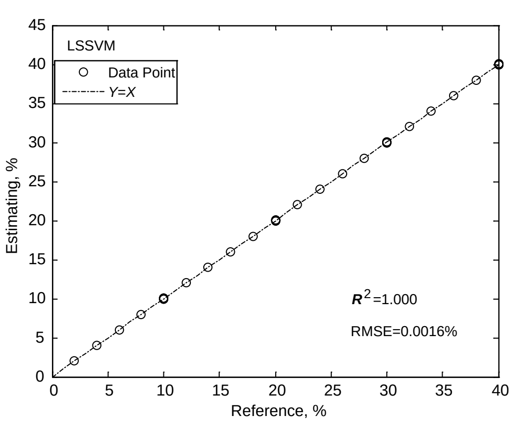

Figure 1: Retrieved SM 1-D mode (L-, H and V, 20 deg).

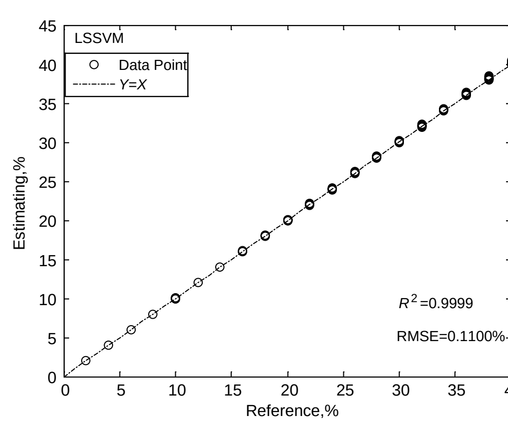

Figure 2: Retrieved SM combined 6.9 GHz with L-2-D modes.

4. RESULTS AND COMPARISON

Through the brightness temperature simulation and numerical experiments, we obtained the retrieval results for the soil moisture, the R^2 between the retrieved SM and the reference, and the RMSE in SM are also given in the Table 2.

As were shown in the figures (part of the results) and Table 2, obviously, we can get the following main conclusions: L-band result is better than C-band in different wavelengths; the result of large angle is better than the small angle within a limited range; the inversion of SM at C-band combined with L-band displayed that 3-D mode is better than 2-D modes. In Table 2, both of those two methods result sound, evidently, LS-SVM method has an advantage over BPNN method.

5. CONCLUSION

In this study, we had come up with the LS-SVM to retrieve the SM from simulated brightness temperature. The result of the design is based on the simulations of Q/H model that is a promising approach to further investigate the sensing of the SM by space-based microwave radiometers such as the AMSR and SMOS.

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