SOIL MOISTURE RETRIEVAL IN AGRICULTURAL FIELDS USING SATELLITE IMAGES FOR WIRELESS SENSOR NETWORK

G.Dhivya
PG Student, Department of Computer Science and Engineering, Roever Engineering College, Perambalur, Tamilnadu, India

M.Tamilselvi
Assistant Professor, Department of Computer Science and Engineering, Roever Engineering College, Perambalur, Tamilnadu, India

Abstract

The aim of this study was to retrieve the moisture content of soil in agricultural fields based on soil characteristics. A nonnegative Eigen value decomposition scheme, together with an adaptive volume scattering model, is extended to an adaptive model-based decomposition (MBD) (Adaptive MBD) model for soil moisture retrieval. Newly proposed decomposition scheme agreed well with expectations based on observed plant structure and biomass levels. The new method was superior in tracking soil moisture dynamics with respect to previous decomposition methods in our study area, with root-mean-square error of soil moisture estimations. The data are continuously coming from a satellite with high speed. Hence, special algorithms are used to process, analyze, and make a decision from that data.

Keywords: *Agricultural fields, soil characteristics, biomass levels, soil moisture dynamics, volume scattering*.

I. Introduction

The SAR signal is known to contain information about the properties of scatterers, not only on surface characteristics such as soil moisture and surface roughness. Soil moisture retrieval from SAR systems having limited viewing capabilities (i.e., single channel, frequency, and incidence angle) is therefore an underdetermined problem, due to the lack of sufficient observations for estimating several unknown parameters (i.e., soil moisture, surface roughness, and vegetation elements). The polarimetric decomposition techniques have shown potential for application to soil moisture retrieval in agricultural areas. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image.

Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too. Image processing systems are becoming popular due to easy availability of powerful personal computer, large size memory devices, graphics software etc. Digital image processing is the use of computer algorithms to perform image processing on digital images.

A. Methodology

Until convergence Iterate

Until stable (= no object move group)

1. Determine the centroid coordinate.
2. Determine the distance of each Object to the centroids
3. Group the object based on minimum distance.

B. Classification

The SVMs algorithm separates the classes of input patterns with the maximal margin hyper plane. This hyper plane is constructed as:

$$f(x) = \langle w, x \rangle + b$$

Where x is the feature vector, w is the vector that is perpendicular to the hyper plane and $b\|w\|^{-1}$ specifies the offset from the beginning of the coordinate system. To benefit from non-linear decision boundaries the separation is performed in a feature space F, which is introduced by a nonlinear mapping φ the input patterns. This mapping is defined as follows:

$$\langle \varphi\ (x_1), \varphi(x_2) \rangle = K(x_1, x_2)\ \forall (x_1, x_2) \in X$$

C. About the Project

POLARIMETRIC synthetic aperture radar (SAR) is a promising remote sensing technique for soil moisture monitoring. The SAR signal is known to contain information about the properties of scatterers, not only on surface characteristics such as soil moisture and surface roughness but also on the structure and properties of the vegetation canopy. Moreover, current space borne SAR technology allows the fine spatial resolution (from meters to tens of meters) and frequent revisit (from days to weeks) that are needed for soil moisture information to have an impact on agricultural management and hydrological predictions. The SAR backscattered signal from vegetated areas is influenced by vegetation covers and soil surface characteristics such as soil moisture and surface roughness. Soil moisture retrieval from SAR systems having limited viewing capabilities (i.e., single channel, frequency, and incidence angle) is therefore an underdetermined problem , due to the lack of sufficient observations for estimating several unknown parameters (i.e., soil moisture, surface roughness, and vegetation elements).

Consequently, prior information or assumptions concerning the characteristics of the vegetation layer are required to reduce the number of unknowns and successfully invert radar backscatter models to estimate soil moisture. Such a prior information or assumptions are generally in the form of site-specific or vegetation-specific parameters (such as vegetation height, phenology, structure, etc.) in empirical and semi empirical models or, alternatively, highly detailed information on vegetation parameters for numerical and theoretical models , which are laborious to collect in the field.

Alternatively, prior assumptions have to be made on the value, range, or probability distribution of one or more of the underlying surface characteristic, as in change-detection methods or statistical probability methods. Multiple-configuration SAR (i.e., concurrent observations at multiple angles and frequencies) is an efficient way to increase the number of SAR observables to solve for soil moisture. Nevertheless, routine time series of multiple-configuration SAR observations having the high temporal frequency required for tracking soil moisture changes are still difficult to obtain.

II. Existing System

Eigen value-based decomposition approaches and the model-based decomposition (MBD) approaches can use previous method. Both methods decompose the measured complex scattering matrix into a combination of a few simple components and therefore are referred to as polar metric decomposition methods. The polar metric decomposition techniques have shown potential for application to soil moisture retrieval in agricultural areas. In-depth study of the soil moisture mechanisms and understanding of the soil moisture transport law has an important practical significance for regional water resources management and the challenge of the water resources scarcity. Using traditional methods of soil moisture monitoring, deep soil layers can be monitored, but continuous monitoring of soil moisture at the regional level cannot be achieved. Although remote sensing simulation models can meet regional scale needs, these models are confined to the surface soil layer, and research on deep soil moisture inversion is still lacking.

This paper focuses on these two issues, and investigates a remote sensing-driven soil moisture monitoring model for the Weihe River Basin. Considering water resource management needs in the Weihe River Basin, it improved the structure of the soil moisture balance model and optimized model parameters to build the remote sensing driven soil moisture balance model (RS-SWBM).

III. Proposed System

Proposed System helps to estimate soil moisture in agricultural crop fields from fully polarimetric L-band synthetic aperture radar (SAR) data through the polarimetric decomposition of the SAR coherency matrix. Newly proposed decomposition scheme agreed well with expectations based on observed plant structure and biomass levels. The satellite image of the agricultural land area in which the soil moisture should be found will be uploaded into the system. After uploading, preprocessing will be done by using median filter. As the result the noise present in the satellite image will be removed and the region was extracted. Again median filter is used for border extraction. The extracted region will be segmented by using segmentation process and the soil was located. Feature extraction will be carried out to compute the soil moisture from the located soil. The graphical image will be got as an output. Finally, performance evaluation will be done to evaluate the performance.

A. Modules Description

1. Image Acquisition

Understanding the strengths and weaknesses of different types of sensor data is essential for the selection of suitable remotely sensed data for image classification. It requires considering such factors as user’s need, the scale and characteristics of a study area, the availability of various image data and their characteristics, cost and time constraints, and the analyst’s experience in using the selected image.

2. Preprocessing

Remote sensing images are uploaded and perform the preprocessing steps to remove the noises from images. We implement the median filter to remove the noise and irrelevant features.

3. Features extraction

Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features . *Clustering*

4. Clustering

In this module, cluster the features which are extracted by previous approach by using K means clustering. This algorithm starts with some clusters of pixels in the feature space, each of them defined by its center.

5. Classification

Classification is done with the help of SVM classifier. In the recent years, SVM classifiers have established excellent performance in a variety of pattern recognition troubles.

6. Evaluation Criteria

We can evaluate the performance of the system using accuracy metric. Proposed system provide improved accuracy rate.

B. Algorithmic Steps for K-Means Clustering

Let X = $\{x_1,x_2,x_3,\ldots\ldots..,x_n\}$ be the set of data points and V = $\{v_1,v_2,\ldots\ldots.,v_c\}$ be the set of centers.

1. Randomly select *'c'* cluster centers.
2. Calculate the distance between each data point and cluster centers.
3. Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.
4. Recalculate the new cluster center using:

$$v_i = (1/c_i)\sum_{j=1}^{c_i} x_i$$

where, *'c_i'* represents the number of data points in i^{th} cluster.

5. Recalculate the distance between each data point and new obtained cluster centers.
6. If no data point was reassigned then stop, otherwise repeat from step 3.

C. Benefits

This resulted in lower and more temporarily stable volume scattering components when compared to previous decomposition models. The use of a nonnegative eigen value approach proved to be ineffective in constraining the volume intensity.

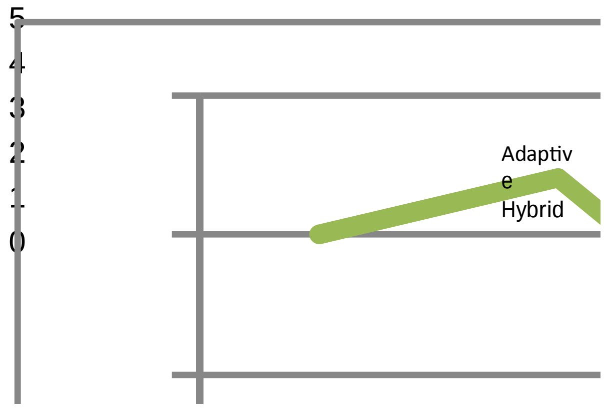

Fig. 1. Time Series Graph

The above graph shows the comparison among three moisture detection and retrieval models which is referred from Soil Moisture Retrieval in Agricultural Fields Using Adaptive Model-Based Polarimetric Decomposition of SAR Data. X axis represents Months and Y axis represents Volume Scattering Intensity. The below table helps to identify the soil moisture in the agricultural fields based on surface roughness scale that is ranked from 0 to 5. Soil moisture will be noted as High, Medium and Low by using the scale levels.

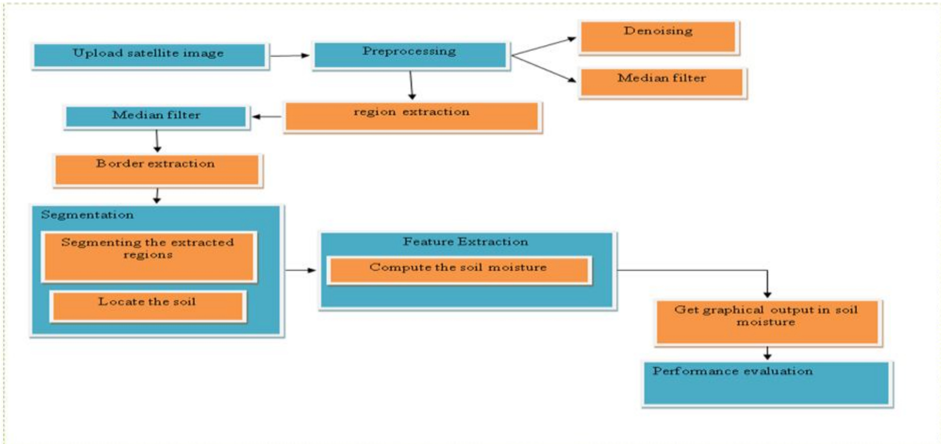

Fig 2. Overall Architecture Diagram

Table 1: Soil Moisture Deflection

Field ID	Crop Grown	Stage	Inversion Rate (%)	Row (Field) Structure	Irrigation Date	Surface Roughness Scale (0 TO 5)	Soil Moisture
1	Wheat	Leaf Emergence	15-25	N-S	01/17	1.6	High
2	Wheat	Leaf Emergence	28-35	E-W	05/17	5	Low
3	Wheat	Stem Elongations	23-35	E-W	06/17	2	Medium
4	Paddy	Leaf Emergence	35-45	N-S	07/17	0	High
5	Paddy	Stem Elongations	37-45	N-S	20/17	3	Medium
6	Corn	Stem Elongations	15-25	E-W	12/17	4	Low

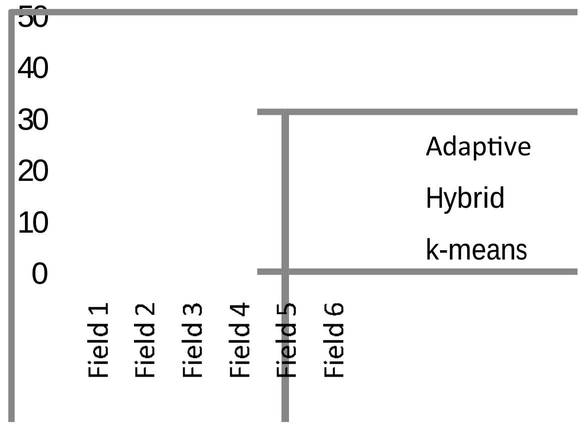

Fig 3. Bar Chart

The above bar chart was drawn by referring the above soil moisture detection table by comparing the three models like adaptive, Hybrid and k-means. In above bar chart x-axis represents Field ID and Y-axis represents Inversion Rate (%).

IV. Conclusion

The data are continuously coming from a satellite with high speed. Hence, special algorithms are needed to process, analyze, and make a decision from that image Data. To analysis soil moisture for agriculture field in real-time satellite image successfully. We conclude that our project provide the accurate image segmentation results using convex SVM classification and K-means algorithm. Our proposed System is good segmentation tool for analyze the user inputs and ability to produce the accurate boundary contour initializations. Our method produces the efficient and very fast method to satellite images segmentation that information's are automatically send to specified user through the network. In future, non-parametric methods such fuzzy clustering, fuzzy logics, etc. will be used.

V. References

1. M. Arii, "Retrieval of soil moisture under vegetation using polarimetric radar," Ph.D. dissertation, Div. Eng. Appl. Sci., California Inst. Technol., Pasadena, CA, USA, 2009.
2. N.Baghdadi et al., "A potential use for the C-band polarimetric SAR parameters to characterize the soil surface over bare agriculture fields," IEEE Trans. Geosci. Remote Sens., vol. 50, no. 10, pp. 3844–3858, Oct. 2012.
3. X. Blaes et al., "C-band polarimetric indexes for maize monitoring based on a validated radiative transfer model," IEEE Trans. Geosci. Remote Sens., vol. 44, no. 4, pp. 791–800, Apr. 2006.
4. S. R. Cloude and K. P. Papathanassiou, "Surface roughness and polarimetric entropy," in Proc. IEEE Int. Geosci. Remote Sens. Symp., Hamburg,Germany, 1999, pp. 2443–2445.
5. Ferrazzoli et al., "The potential of multifrequency polarimetric SAR in assessing agricultural and arboreous biomass," IEEE Trans. Geosci. Remote Sens., vol. 35, no. 1, pp. 5–17, Jan. 1997.

6. A. Freeman and S. L. Durden, “A three-component scattering model for polarimetric SAR data,” IEEE Trans. Geosci. Remote Sens., vol. 36, no. 3, pp. 963–973, May 1998.
7. I. Hajnsek, E. Pottier, and S. R. Cloude, “Inversion of surface parameters from polarimetric SAR,” IEEE Trans. Geosci. Remote Sens., vol. 41,no. 4, pp. 727–744, Apr. 2003.
8. A. Iodice, A. Natale, and D. Riccio, “Retrieval of soil surface parameters via a polarimetric two-scale model,” IEEE Trans. Geosci. Remote Sens.,vol. 49, no. 7, pp. 2531–2547, Jul. 2011.
9. A. Iodice, A. Natale, and D. Riccio, “Polarimetric two-scale model for soil moisture retrieval via dual-pol HH-VV SAR data,” IEEE J. Sel.Topics Appl. Earth Observ. Remote Sens., vol. 6, no. 3, pp. 1163–1171, Jun. 2013.
10. M. Jia, L. Tong, Y. Zhang, and Y. Chen, “Multitemporal radar backscattering measurement of wheat fields using multifrequency (L, S, C, and X) and full-polarization,” Radio Sci., vol. 48, no. 5, pp. 471–481, 2013.
11. Lian He, Rocco Panciera, Member, IEEE, Mihai A. Tanase, Member, IEEE, Jeffrey P. Walker, Member, IEEE, and Qiming Qin “Soil Moisture Retrieval in Agricultural Fields Using Adaptive Model-Based Polarimetric Decomposition of SAR Data”
12. F. Mattia et al., “Multitemporal C-band radar measurements on wheat fields,” IEEE Trans. Geosci. Remote Sens., vol. 41, no. 7, pp. 1551–1560, Jul. 2003.
13. O. Merlin et al., “Soil moisture measurement in heterogeneous terrain,” in Proc. Int. Congr. MODSIM, Christchurch, New Zealand, 2007, pp. 2604–2610.
14. S.-E. Park, W. M. Moon, and D.-J. Kim, “Estimation of surface roughness parameter in intertidal mudflat using airborne polarimetric SAR data,” IEEE Trans. Geosci. Remote Sens., vol. 47, no. 4, pp. 1022–1031,Apr. 2009.
15. D. L. Schuler, J.-S. Lee, D. Kasilingam, and G. Nesti, “Surface roughness and slope measurements using polarimetric SAR data,” IEEE Trans. Geosci. Remote Sens., vol. 40, no. 3, pp. 687–698, Mar. 2002.
16. W. F. Silva, B. F. T. Rudorff, A. R. Formaggio, W. R. Paradella, and J. C. Mura, “Discrimination of agricultural crops in a tropical semi-arid region of Brazil based on L-band polarimetric airborne SAR data,” ISPRS J. Photogramm. Remote Sens., vol. 64, no. 5, pp. 458–463, 2009.
17. H. S. Srivastava, P. Patel, M. L. Manchanda, and S. Adiga, “Use of multi-incidence angle RADARSAT-1 SAR data to incorporate the effect of surface roughness in soil moisture estimation,” IEEE Trans. Geosci. Remote Sens., vol. 41, no. 7, pp. 1638–1640, Jul. 2003.
18. J. J. Van Zyl, “Unsupervised classification of scattering behavior using radar polarimetry data,” IEEE Trans. Geosci. Remote Sens., vol. 27, no. 1, pp. 36–45, Jan. 1989.
19. J. J. van Zyl, M. Arii, and K. Yunjin, “Model-based decomposition of polarimetric SAR covariance matrices constrained for nonnegative eigenvalues,” IEEE Trans. Geosci. Remote Sens., vol. 49, no. 9, pp. 3452–3459, Sep. 2011.
20. M. Zribi, O. Taconet, V. Ciarletti, and D. Vidal-Madjar, “Effect of row structures on radar microwave measurements over soil surface,” Int. J. Remote Sens., vol. 23, no. 24, pp. 5211–5224, 2002.