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MACHINE LEARNING ALGORITHMS TO RETRIEVE SOIL MOISTURE USING GROUNDWATER DATASET

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Abstract: In this paper, the AMSR-E brightness temperatures are used to train SVM & KNN for the prediction of the European centre for medium-range weather forecasts (ECMWF) model. Compared with the classical inversion methods, the Machine Learning-based method is more suitable for global soil moisture retrieval. It is very well supported by graphics processing unit (GPU) acceleration, which can meet the demand of massive data inversion. Once the model trained, a global soil moisture map can be predicted in less than 10 seconds. What's more, the method of soil moisture retrieval based on Machine learning can learn the complex texture features from the big remote sensing data. In this experiment, the results demonstrates that the SVM & KNN deployed to retrieve global soil moisture can achieve a better performance than the support vector regression (SVR) for soil moisture retrieval suited for parallel implementation on programmable DSP processors.

INTRODUCTION

Soil moisture plays a crucial role in various agricultural, hydrological, and environmental applications. Traditional methods for soil moisture retrieval often rely on in-situ measurements, which can be time-consuming and expensive. In recent years, machine learning techniques have emerged as a promising approach to estimate soil moisture using remote sensing data. However, most existing studies focus on using satellite-based observations, neglecting the valuable information provided by groundwater levels. This study proposes a novel approach for soil moisture retrieval using machine learning, specifically leveraging ground water data. The goal is to exploit the relationship between groundwater levels and soil moisture content to develop a reliable and accurate estimation model. A empirical model is established to analyse the daily retrieval of soil moisture from passive microwave remote sensing using convolutional neural networks (CNN). Soil moisture plays an important role in the water cycle. However, with the rapidly increasing of the acquiring technology for remotely sensed data, it's a hard task for remote sensing practitioners to find a fast and convenient model to deal with the massive data.

PROBLEM STATEMENT

Support vector regression (SVR) is a popular approach in the field of geo-/bio-physical parameter retrieval, which however only has the good intrinsic generalization ability and the robustness to noise in the case of limited availability of the reference samples (Durbha et al., 2007). In addition, traditional models is not flexible enough to learn more about feature information. Therefore, it is of great advantage to investigate deep learning based soil moisture retrieval approach in comparison with classical algorithms.

DISADVANTAGES

- Performance is low

PROPOSED SYSTEM

This paper uses Machine learning in the inversion of soil moisture content, which can learn the complex features from the big remote sensing data better and retrieve soil moisture in real time compared with classical algorithms. The SVM & KNN algorithm used in this research is composed of three pairs of convolution layers and pooling layers with one fully connected layer on top, whose activation function of the top layer is changed from softmax loss layer to Euclidean loss layer. The AMSR-E brightness temperature images are used as input, and the soil moisture value gained from ECMWF model which is considered the most accurate value of soil moisture content is used as ground truth. In this experiment, one month’s global data which include 30 pairs of images is used to train the Machine learning model, and then it is used to predict the next month’s data for soil moisture maps. By comparing the root-mean square error (RMSE) and the R-square

(R^2) with SVM, the experiment demonstrates the Machine learning method for soil moisture retrieval can achieve better learn the complex relationship between the observations and the ground truth and achieve better generalization performance compared with traditional retrieval algorithms.

ADVANTAGES

- Demand of massive data inversion. Once the model trained, a global soil moisture map can be predicted in less than 10 seconds. What's more, the method of soil moisture retrieval based on machine learning can learn the complex texture features from the big remote sensing data. In this experiment, the results demonstrates that the SVM & KNN deployed to retrieve global soil moisture can achieve a better performance than the support vector regression (SVR) for soil moisture retrieval.

LITERATURE SURVEY

- **1. The smos soil moisture retrieval algorithm. IEEE Transactions on Geoscience & Remote Sensing:**

- The Soil Moisture and Ocean Salinity (SMOS) mission is European Space Agency (ESA's) second Earth Explorer Opportunity mission, launched in November 2009. It is a joint program between ESA Centre National d'Etudes Spatiales (CNES) and Centro para el Desarrollo Tecnologico Industrial. SMOS carries a single payload, an L-Band 2-D interferometric radiometer in the 1400-1427 MHz protected band. This wavelength penetrates well through the atmosphere, and hence the instrument probes the earth surface emissivity. Surface emissivity can then be related to the moisture content in the first few centimeters of soil, and, after some surface roughness and temperature corrections, to the sea surface salinity over ocean. The goal of the level 2 algorithm is thus to deliver global soil moisture (SM) maps with a desired accuracy of 0.04 m3/m3. To reach this goal, a retrieval algorithm was developed and implemented in the ground segment which processes level 1 to level 2 data. Level 1 consists mainly of angular brightness temperatures (TB), while level 2 consists of geophysical products in swath mode, i.e., as acquired by the sensor during a half orbit from pole to pole. In this context, a group of institutes prepared the SMOS algorithm theoretical basis documents to be used to produce the operational algorithm. The principle of the SM retrieval algorithm is based on an iterative approach which aims at minimizing a cost function. The main component of the cost function is given by the sum of the squared weighted differences between measured and modeled TB data, for a variety of incidence angles. The algorithm finds the best set of the parameters, e.g., SM and vegetation characteristics, which drive the direct TB model and minimizes the cost function. The end user Level 2 SM product contains SM, vegetation opacity, and estimated dielectric constant of any surface, TB computed at 42.5°, flags and quality indices, and other parameters of interest.

- **2. Assessment of QP model based two channel algorithm with JAXA, LPRM soil moisture products over Genhe area in China**
- QP model with dual-channel algorithm could accurately represent the effect of surface roughness on emission at different polarization under big view angle. The purpose of this paper is to estimate long temporal series soil moisture product based on the QP algorithm, and compared it with JAXA, LPRM in Genhe basin. The results indicate that QP retrieval values are closest to the ground data but it have many missing values and high RMSE (around 0.15$m^3 m^{-3}$); JAXA product has good correlation coefficients (around 0.4) but underestimates the ground data. LPRM product overestimates the ground data and it is found to be very noisy and unstable. Finally, In order to improve the model, this paper analysed the tendency of QP retrievals with satellite brightness temperature, and examined the

influence of auxiliary data for retrievals.

- **3. Soil moisture retrieval from amsr-e and ascat microwave observation synergy**
- A study is performed to analyze the daily retrieval of soil moisture from the synergy of active and passive microwave data using observations from
  the ASCAT scatterometer and AMSR-E radiometer. The objective is to identify the information provided by each sensor and to analyze preprocessing methods – such as the day/night average, diurnal difference and microwave polarization difference index for AMSR-E and the incidence angle normalization and backscatter temporal index for ASCAT – to maximize the amount of soil moisture information extracted. Additionally, the data fusion and a posteriori synergy methodologies are compared to determine how to optimally exploit this combined information.

MODULE DESCRIPTION

Preprocessing of the Images

All the images employed to train CNN model need to be reprocessed, and the major steps includes image registration, spatial interpolation, and normalization. Because the one day's data cannot overlap the whole world, it was a vital step to registrate 1-2 day's AMSR-E data for obtaining the average images. In addition, the brightness temperature data and soil moisture truth value from ECMWF had different resolution. In this paper, the soil moisture truth value images grid with a 0.5° resolution have been projected onto an equal area grid with a 0.25° resolution the same as brightness temperature data. Then the inputs and outputs are normalized to [0,1].After e processing, many patch images of size 9×9 were generated.

Run SVM Algorithm:

Using this module we will split dataset into train and test and then build SVM trained model. Trained model will be applied on test data to calculate and test prediction accuracy.

Run KNN Algorithm:

Using this module we will split dataset into train and test and then build KNN trained

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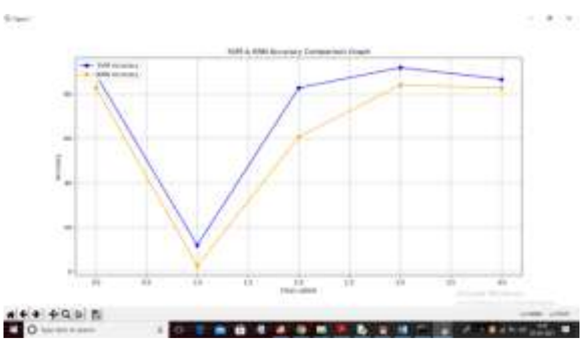
model. Trained model will be applied on test data to calculate and test prediction accuracy.

SAMPLE RESULTS



CONCLUSION

In this project, a KNN has been employed to AMSR-E brightness temperatures images to retrieve the global soil moisture daily. The KNN used took the image patches of brightness temperature data as input and output soil moisture value directly. When compared to classical SVR approach, the KNN method achieved soil moisture results that are closer to the ground truth map. The training on 31 images took about 2 hours, the prediction of soil moisture on one image took less than 10 seconds using an Nvidia GTX 1080Ti graphics card. With more powerful or more quantity graphics cards, the time spent on training and predicting will be reduced largely. Once the model between the brightness temperature and soil moisture trained, the soil moisture retrieval can run in parallel and multiple GPUs easily. However, the prediction of soil moisture on one image using SVR took more than two minutes. Therefore, comparing with traditional regression approaches, KNN had a great advantage on both prediction accuracy and computational cost for the retrieval of soil moisture from big remote sensing data.

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