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Soil pH Formulation by its Moisture Using Dyadic Wavelet Transform

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***Abstract**: This paper aims at developing a hardware module for monitoring the soil macronutrient content to achieve high yield in agricultural field. This can be done by analyzing the spectral characteristics of soil image. The acquired image is processed to obtain the dielectric properties of soil. Itis involved to find the basic properties of soil. It also revolves around to measure the pH value of the soil by retrieving the moisture content of it. To formulate this dyadic wavelet transform is being used. This is tested with different landscapes to estimate the pH of soil.The different landscapes which is being considered by adding small, medium and large amount of fertilizers in it. Then calculate the pH level of those landscapes soil which is being treated by fertilizerslike potassium and urea. By estimating the pH value of the soil it is possible to avoid the circumstances of the barren agricultural field.*

***Index Terms**: Dyadic wavelet transform, Filtering, Data Acquisition, Soil pH.*

I. Introduction

Soil plays an important role in the agricultural field for cultivating the crops. In recent surveyit has been proved that 2/3 of the agricultural field has been devastated due to over consumption the fertilizers like potassium, Urea etc. Due to these reasons manyproductivity of lands being turned into barren land. To overcome this situation, the proposed method proceedswith formulating the pH of the soil there by predict that whether the land has consumed little or large quantity of fertilizers. Soil is recognized as one of the most valuable natural resource whose soil pH property used to describe the degree of acidity or basicity which affect nutrient availability and ultimately plant growth. Soil colour is visual perceptual property corresponding in humans to the categories i.e red, green, blue and others. Soil colours are the parts of visual perceptual property where digital values of red, green and blue (RGB) provide a clue for spectral signature capture of different pH in soil. For the capturing images, digital camera was used.

Colourconsistencymeans that an image of an object should have the samecolour regardless of the ambient lighting conditions. Factors affecting thecolour of an object are; inhomogeneous illumination,colour temperature, and image noise. Any image can be transferred toacommon norms by correcting colourtemperature and inhomogeneous illumination. Image noise, however it is random and cannot be corrected .In order to reduce the image noise level prefer high end cameras and a powerful light sourcewhichsuppress the image noise sufficiently go with usage of low pass filter which also have the ability of reducing the image noise level.The process to estimate the pH of soil carried out by different modules which includesi.Dataacquisitionii.Filteringprocessiii. Wavelet transformiv.Texture Analysis. The high end camera have been used to capture the image of the soil here Logitech quickcam has been preferred to segment the RGB colour band.Second module followed with Data acquisition ,the physical parameters of the soil such as pressure, temperature, moisture is being converted to binary form i.e digital form which is acceptable by computer.

In filtering processthe image noise have been removed by low pass filter.Third module is working of dyadic wavelet transform and reconstruction of dyadic wavelet transform which it brings out the projected image of the soil. Fourth module followed with the Texture analysis and which it produces the Local Binary Pattern image in RGB color band and histogram diagram is being obtained and by which calculating the average value of those histogram diagram calculate the pH value of the soil.The histogram diagram will be changing for different fertilizers and calculating those differences to estimate pH value of the soil which is being treated with respective fertilizers.In existing system soil analysis is by using Near Infrared Radar(NIR) sensor where the nutrient content in the soil was detected by the spectral characteristics of NIR in which each macronutrient reflects the infrared waves at a certain defined wavelength according to its atomic structure. The reflected signal is processed to detect the presence of nutrient content in the soil.Retrieving soil moisture from Spaceborne radar observations is proceeds with number of observations from a particular radar sensor which is less than the unknown surface parameters. These parameters include multiple scales of roughness and potentially several vegetation characteristics. In order to address these issues, several approaches have been developed using a combination of theory and empiricism based on ground-based, airborne, and spaceborne radar observations.Y. Inoue et.al[1] describes the method to analyze the sensitivity of very high resolution TerraSAR-X radar data taken over bare soils to surface soil parameters and to study the spatial variability of these parameters at a fine scale (within a field plot). The relationship between the backscattering coefficient and the soil's parameters (moisture, surface roughness, texture, and local topography) was examined by means of four satellite images, as well as ground truth measurements, of each of the three agricultural plots, recorded during several field campaigns in the winter and spring of 2008. TerraSAR images demonstrate high potential for the identification of local variations of roughness and texture. An approach for the estimation of local moisture is proposed using an empirical method adapted to the scale of an individual field. The results shown that, by using TerraSAR-X data to study bare agricultural fields, local variations in soil moisture can be retrieved with a root-mean-square error of 0.05 cm.

S.A Tabatabaeenejad [2]which describes about the2-D vector-element-based finite-element method (FEM) is used to calculate the radar backscatter from 1-D bare rough soil surfaces which can have an underlying heterogeneous substrate. Monte Carlo simulation results are presented for scattering at L-band ($\lambda = 0.24$ m). For homogeneous soils with rough surfaces, the results of FEM are compared with the predictions of the small perturbation method. In the case of heterogeneous substrates, soil moisture (and, hence, soil permittivity) is assumed to vary as a function of depth. In this case, the results of FEM are compared with those of the transfer matrix method for flat soil surfaces. In both cases, a good agreement is found. For homogeneous rough soils, it is found that polarimetric radar backscatter and copolarized phase difference have a nonlinear relationship with soil moisture. Finally, it is found that the nature of the soil moisture variation in the top few centimeters of the soil has a strong influence on the backscatter and, hence, on the inferred soil moisture content

YM Aubert[3] which describes about thepotential of high-resolution radar imagery to estimate various hydrological parameters, such as soil moisture, has long been recognized. Image simulation is one approach to study the interrelationships between the radar response and the underlying ground parameters. In order to perform realistic simulations, the authors incorporated the effects of naturally occurring spatial variability and spatial correlations of those ground parameters that affect the radar response, primarily surface roughness and soil moisture. R.Akbar-[4] which describes about a framework for surface soil moisture estimation is presented in this work wherein bothradar backscatter and radiometer brightness temperature measurements are effectively and simultaneously utilized. Within this combined estimation approach a regularization parameter is also introduced enabling the algorithm to perform radar-only, radiometer-only or joint radar-radiometer soil moisture retrieval when necessary.

D. Entekhabi [5] describes the methodthat Soil Moisture Active Passive (SMAP) mission is one of the first Earth observation satellites being developed by NASA in response to the National Research Council's Decadal Survey. SMAP will make global measurements of the soil moisture present at the Earth's land surface and will distinguish frozen from thawed land surfaces. Direct observations of soil moisture and freeze/thaw state from space will allow significantly improved estimates of water, energy, and carbon transfers between the land and the atmosphere. The accuracy of numerical models of the atmosphere used in weather prediction and climate projections are critically dependent on the correct characterization of these transfers. Soil moisture measurements are also directly applicable to flood assessment and drought monitoring. SMAP observations can help monitor these natural hazards, resulting in potentially great economic and social benefits. SMAP observations of soil moisture and freeze/thaw timing will also reduce a major uncertainty in quantifying the global carbon balance by helping to resolve an apparent missing carbon sink on land over the boreal latitudes.

Y. Oh [6] describes about a multilayer soil model for retrieving soil moisture content using the Integral Equation Method (IEM) is investigated in this paper. The total reflection coefficients of the natural soil are obtained using the multilayer model, and volumetric scattering is approximated by the internal reflections between layers. The surface reflection terms in IEM model are replaced by the total reflection coefficients from the multi-layer soil surface in retrieving the soil moisture content.The original IEM model includes only the surface scattering of the natural bare soil, while the multilayer soil - IEM model (MS-IEM) includes both the surface scattering and the volumetric scattering within the soil. Both the MS-IEM model and the original IEM model are compared in soil moisture retrieval using the experimental Synthetic Aperture Radar (SAR) backscattering coefficient data in the literature. It is noted that the mean square error between the measurement data and the values estimated by the modified IEM model is about 7.7%, while that between the measured and the estimated by the original IEM model is about 12%. The accuracy of estimating soil moisture by the IEM model is improved by 4.3%. In addition, the regression analysis between the measured and model-predicted soil moistures has been doneM. Zribietal [7]explains about a new empirical model for the retrieval, at a field scale, of the bare soil moisture content and the surface roughness characteristics from radar measurements is proposed. The derivation of the algorithm is based on the results of three experimental radar campaigns conducted under natural conditions over agricultural areas. Radar data were acquired by means of several C-band space borne (SIR-C, RADARSAT) or helicopter borne (ERASME) sensors, operating in different configurations of polarization (HH or VV) and incidence angle. Simultaneously to radar acquisitions, a complete ground truth data base was built up with different surface condition measurements of the mean standard deviation (rms) height s, the correlation length l, and the volumetric surface moisture.M. M. Rahmanet al., [8] describes about the surface roughness is a key parameter of radar backscatter models designed to retrieve surface soil moisture (thetaS) information from radar images. This work offers a theory-based approach for estimating a key roughness parameter, termed the roughness correlation length (L c). The L c is the length in centimeters from a point on the ground to a short distance for which the heights of a rough surface are correlated with each other. The approach is based on the relation between L c and h RMS as theorized by the Integral Equation Model (IEM).This new approach opens up the possibility of determining both roughness parameters without ancillary data based on the radar backscatter difference measured for two different incident angles.

II. Proposed System

Physically, the wavelength of light determines its color. The color of anobject is determined both by the spectrum of the incident illumination andon the reflectance spectrum of the surface. Color space, also known as thecolor model (or color system), is an abstract mathematical model which simply describes the range ofcolors as tuples of numbers, typically as 3 or 4 values or color components Some examples are RGB (red, green, and blue),CMYK (cyan, magenta, yellow, and black), and HSV (hue, saturation, andvalue). The RGB color space model is the one which is used by most of the digital camerasand computer screens, remainingcolors can be represented by mixing variousamounts of red, green, and blue to it. By mixing of those colorsdescribe nearly16581375 different colors.Human perception of color is highly influenced by in-brain image analysis. Using the reflection of the soil and by its colour, pH can be estimated.

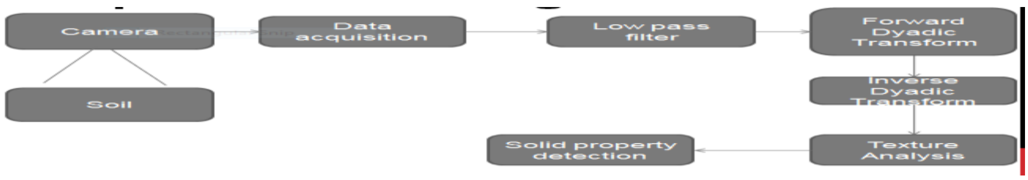


Figure. Block diagram

Data Acquistion

The core of any image acquisition application is the data acquired from the input device. A trigger is the event that initiates the acquisition of image frames, a process called logging. A trigger event occurs when a certain condition is met. For some types of triggers, the condition can be the execution of a toolbox function. For other types of triggers, the condition can be a signal from an external source that is monitored by the image acquisition hardware.

Low Pass Filter

A low-pass filter is a filter that allows signals below a cutoff frequency (known as the passband) and attenuates signals above the cutoff frequency (known as the stopband). By removing some frequencies, the filter creates a smoothing effect. That is, the filter produces slow changes in output values to make it easier to see trends and boost the overall signal-to-noise ratio with minimal signal degradation.Low-pass filters, especially moving average filters or Savitzky-Golay filters, are often used to clean up signals, remove noise, perform data averaging, design decimators and interpolators, and discover important patterns.

Dyadic Wavelet Transform

Two-dimensional dyadic wavelet transform (2D-DWT) is defined by an approximation component,two detail components in horizontal and vertical directions. The reference [1] introduces a new type of two-dimensional dyadic wavelet transform and its application so that dyadic wavelet can be studied and used widely furthermore. (1) Two-dimensionalstationary dyadic wavelet transform (2D-SDWT) is proposed, it is defined by approximation coefficients, detail coefficients in horizontal, vertical and diagonal directions,which is essentially the extension of two-dimensional stationary wavelet transform for orthogonal/biorthogonal wavelet filters. (2) ε-decimated dyadic discrete wavelet transform (DDWT) is introduced and its relation with 2D-SDWT is given, where ε is a sequence of 0's and 1's. (3) Mallat decomposition algorithm based on dyadic wavelet is introduced as a special case of ε-decimated DDWT, and so a face recognition algorithm based on dyadic wavelet is proposed, and experimental results are given to show its effectiveness.

Inverse Dyadic Transform

The decomposition procedure is different from previous method in that the scaling of the wavelet is not achieved by subsampling of the image in each step, but rather by aupsampling of the filters. Redundant wavelet transform at scale j decomposes f(x,y) into three wavelet subbands used to easily segmentRGB color band.

An approximation band $S_j f(x, y) = f * \phi_j(x, y)$,

A horizontal detail band $W_j^1 f(x, y) = f * \psi_j^1(x, y)$

A vertical detail band $W_j^2 f(x, y) = f * \psi_j^2(x, y)$.

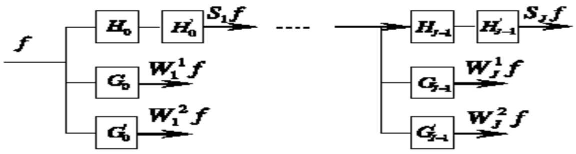
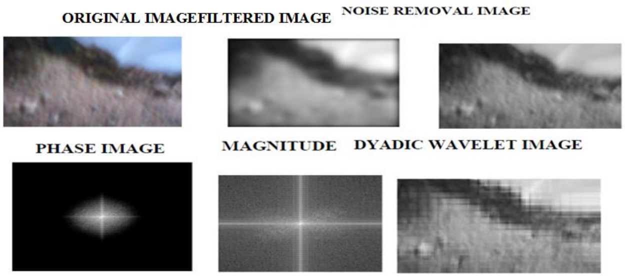


Figure:redundant wavelet transform

III. Experimental Results



The original image of the soil which is captured by the Logitech Quickcam.Thefiltered image is the gray scale image which is transformed from the original image in order to point out the noise in the image.The phase image of the soil acquired during removal of noise from the soil.The magnitude image of the soil acquired during removal of noise from the soil.The dyadic wavelet transform occurred during wavelet processing can easily segment RGB color band.

IV. Conclusion

A simple formulation based on heritage and established relationships is used to represent backscatter dependence on soil moisture for limiting cases defined by three end-members: 1) end-member I or smooth bare soils; 2) end-member II or rough soils; and 3) end member III or maximum vegetation cover. These end-members are used to envelop backscatter expected for intermediate land use and land cover. In order to make the approach independent of ancillary data, used the (RV I) formed from radar measurements alone to account for the variable vegetation effect.New (RRI)also formed from radar observations alone to account for variable roughness effects. The RV I and RRI scale the model parameters between the end-members. They only depend on radar backscatter observations and do not require ancillary data on vegetation and roughness. The soil of the image is captured using the camera and by filtering the image the noise is removed from it and then proceed with the working of the dyadic wavelet transform and the image is projected and it is reconstructed and by texture analysis the RGB color band is segmented and the pH value of the soil is predicted by the histogram diagram and followed by their corresponding LBP image is displayed.Future development is the use ofautomated image analysis to study dynamic processes, e.g., solute transportor root growth. Especially interesting is automatedimage analysis for soil classification and studies where pore scale soilproperties are related to macroscopic features like water retention or soilfertility.

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