A Review on Image based Soil Classification

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Abstract— This paper presents a review on image based soil classification techniques. In previous Classification methods there is requirement of an expert who observes the magnitude and trends of the signals in addition to any a priori information that might be available. In this paper an approach for automating this classification procedure is presented. There are methods available such as segmentation algorithm from which the salient features of these segments are extracted using boundary energy method. Based on the measured data and extracted features classifiers assign classes to the segments. They employ Decision Trees, ANNs and Support Vector Machines. In this first features extraction methods of image processing is applied to extract the features of soil sample images. Then database of sample images will be prepared and classification of soil will be done Using Support Vector Machine algorithm.

Key words: Soil Classification, Cone Penetration Test, Image Processing, Support Vector Machine

I. Introduction

There is a necessity to classify contiguous intervals (segments) of series data (signals) in a number of engineering problems. Series data has an additional index variable (distance or time) associated with each data value. In standard classification algorithms these situations are often inadequate due to the additional contiguity constraint.

Examples are from the following domains: classification of sub-soil layers using Cone Penetration Testing [2], in petroleum engineering, paleoecology, etc. In these cases measurements are taken from a vertical bore or employing test apparatus that is pushed down the earth and stratigraphically information is preserved in the classification. The problem is solved in two phases: firstly, a segmentation algorithm is utilize to cluster contiguous blocks of instances and then, these segments are classified by domain experts. To automating classification of soil layers from measured data is important. In civil engineering it is a prerequisite to know the soil classes up to some depths prior to any construction. The direct method to identify the soil classes by drilling boreholes and testing soil samples is very expensive. A cheaper alternative is the so-called Cone Penetration Testing (CPT). CPT is one of the most popular soil investigation methods [2]. But all these methods require manual data of soil samples and for classification using expert advice is difficult and expensive also. Different results also occurred due to different expert give result as per their knowledge. For these difficulties or to remove these limitations algorithm can be formed which work efficiently. Which is based on image processing?

II. Literature review

Nathan P. Odgers and Alex. B. Mc Bratney, 2018 presents a paper for Soil classification is really about answering the question what makes a soil? Or, perhaps, what makes one soil different from another? To answer questions like these, soil classifiers create taxonomic rules to separate one kind of soil from another and categorise and make sense of the diverse pattern of the soil continuum. Traditionally a great deal of consideration has been given to characterising and classifying the whole soil profile in a top-down fashion. Pedometric methods allow us to answer the same questions in a bottom-up trajectory. Thus, the starting point is not the whole soil profile or even its major constituents, the soil horizons. Rather we start by classifying the actual, tangible, skeleton of soil itself: the soil material.

Jordan et al 2018 presents a paper for this study demonstrates the use of digital image processing for the spatial pattern recognition and characterisation of Ni concentrations in topsoil in Europe. Moving average smoothing was applied to the TIN-interpolated grid model to suppress small irregularities. Digital image processing was applied then to the grid. Several NE-SW, E-W and NW-SE oriented features were revealed at the continental scale. The dominant NE-SW linear features follow the Variscan and Alpine orogenies. The highest variability zones are in the Alps and the Balkans where mafic and ultramafic rocks outcrop. A single major E-W oriented north-facing feature runs along the last continental glaciation zone. This zone also coincides with a series of local maxima in Ni concentration along the glaciofluvial deposits. The NWSE elongated features are located in the Pyrenees, northern Italy, Hellas and Fennoscandia. This study demonstrates the advantages of digital image processing analysis in identifying and characterising spatial geochemical patterns unseen before on conventional colour-surface maps.

S. K. Honawad 2017 investigates the development of digital image analysis approach for estimation of physical properties of soil in lieu of conventional laboratory approach. The traditional laboratory approach attracts some drawbacks such as lot of manual involvement, time consuming, chances of creeping of human errors, uncertain prediction and always invasive in nature. The signal processing methods involve enhancing original image using filters and calculating the features of the transformed images. In this paper Low mask, Gabor Filter and color quantization are applied to the original images to extract the texture features of soil images for retrieval. Results on a database of 100 soil images belonging to 10 different types of Soils with different orientations, scales and translations shows that proposed method performs retrieval efficiency effectively. The features are constructed on pre-processed methods applied on the Soil texture image by considering different types of windows. These features offer a better classification rate.

Dornik 2017 we used eighteen digital elevation model derivatives and five remote sensing indices, related to vegetation cover and soil. Using 171 soil profiles with associated values of environmental variables, Random forests (RF) method was applied to identify the most important soil type predictors for use in the segmentation process. The stack of raster-geodatasets corresponding to the selected predictors was segmented with multi-resolution segmentation algorithm resulting in homogeneous objects related to soil types. These objects were further classified as soil types using the same method, RF. Also we conducted a pixel-based classification, using the same classifier and the same soil samples. Resulting maps were assessed in terms of their accuracy using 30% of the soil profiles for validation. The main result of this study shows that GEOBIA is a valid and beneficial method for soil type mapping, leading to improvements over the pixel-based approach. The optimized object-based soil map has an overall accuracy of 58% being 10% higher than the optimized pixel-based map.

Srunitha.k 2016 presented Classification of soil is the dissolution to soil sets to particular group having a like characteristics and similar manners. Almost all countries do product exporting, in which those countries exporting higher agricultural product are very much depend on the soil characteristics. Thus, soil characteristics identification and classification is very much important.

Identification of the soil type helps to avoid agricultural product quantity loss. A classification for engineering purpose should be based mainly on mechanical properties. This paper explains support vector machine based classification of the soil types. Soil classification includes steps like image acquisition, image preprocessing, feature extraction and classification. The texture features of soil images are extracted using the low pass filter, Gabor filter and using color quantization technique. Mean amplitude, HSV histogram, Standard deviation are taken as the statistical parameters.

Qian 2015 published This study evaluates and compares the performance of four machine learning classifiers—support vector machine (SVM), normal Bayes (NB), classification and regression tree (CART) and K nearest neighbor (KNN)—to classify very high resolution images, using an object-based classification procedure. In particular, we investigated how tuning parameters affect the classification accuracy with different training sample sizes. We found that: (1) SVM and NB were superior to CART and KNN, and both could achieve high classification accuracy (>90%); (2) the setting of tuning parameters greatly affected classification accuracy, particularly for the most commonly-used SVM classifier; the optimal values of tuning parameters might vary slightly with the size of training samples; (3) the size of training sample also greatly affected the classification accuracy, when the size of training sample was less than 125. Increasing the size of training samples generally led to the increase of classification accuracies for all four classifiers. In addition, NB and KNN were more sensitive to the sample sizes. This research provides insights into the selection of classifiers and the size of training samples. It also highlights the importance of the appropriate setting of tuning parameters for different machine learning classifiers and provides useful information for optimizing these parameters.

III. Conclusion

The different techniques for soil classification have been studied. A cross validation has been performed using the features mentioned in the literature. Analysis of the results reveals that SVM achieves above 98% accuracy over a set of 224 test images using ten-fold cross validation, where Bayesian classifier accuracy is above 95% over the same set of images. To enable further increase in the classification rate, our future task will involve making the image pre-processing steps more robust to noises.

References

[1] Pu, R.; Landry, S.; Yu, Q. Object-based urban detailed land cover classification with high spatial resolution ikonos imagery. Int. J. Remote Sens. 2011, 32, 3285–3308.

[2] Malinverni, E.S.; Tassetti, A.N.; Mancini, A.; Zingaretti, P.; Frontoni, E.; Bernardini, A. Hybrid object-based approach for land use/land cover mapping using high spatial resolution imagery.Int. J. Geogr. Infor. Sci. 2011, 25, 1025–1043.

[3] Zhang, X.; Feng, X.; Jiang, H. Object-oriented method for urban vegetation mapping using ikonos imagery. Int. J. Remote Sens. 2010, 31, 177–196.

[4] Myint, S.W.; Gober, P.; Brazel, A.; Grossman-Clarke, S.; Weng, Q. Per-pixel vs. object-basedclassification of urban land cover extraction using high spatial resolution imagery. Remote Sens.Environ. 2011, 115, 1145–1161.

[5] Duro, D.C.; Franklin, S.E.; Dube, M.G. A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery. Remote Sens. Environ. 2012, 118, 259–272.

[6] Blaschke, T. Object based image analysis for remote sensing. ISPRS J. Photogramm. Remote Sens.2010, 65, 2–16.

[7] Zhou, W.; Cadenasso, M.L.; Schwarz, K.; Pickett, S.T. Quantifying spatial heterogeneity in urban landscapes: Integrating visual interpretation and object-based classification. Remote Sens. 2014, 6, 3369–3386.

[8] Zhou, W.; Troy, A. An object-oriented approach for analysing and characterizing urban landscape at the parcel level. Int. J. Remote Sens. 2008, 29, 3119–3135.

[9] Laliberte, A.S.; Koppa, J.; Fredrickson, E.L.; Rango, A. Comparison of nearest neighbor and rule-based decision tree classification in an object-oriented environment. In Proceedings of the IEEE International Geoscience and Remote Sensing, Denver, CO, USA, 31 July–4 August 2006.

[10] Laliberte, A.S.; Rango, A.; Havstad, K.M.; Paris, J.F.; Beck, R.F.; McNeely, R.; Gonzalez, A.L. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in Southern New Mexico. Remote Sens. Environ. 2004, 93, 198–210.