Computers and Electronics in Agriculture 148 (2018) 217–225

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Characterizing soil particle sizes using wavelet analysis of microscope images

Bharath Sudarsan[a], Wenjun Ji[a], Viacheslav Adamchuk[a], Asim Biswas[b,*]

[a] Department of Bioresource Engineering, McGill University, 21111 Lakeshore Road, Ste-Anne-de-Bellevue, Quebec H9X 3V9, Canada
[b] School of Environmental Sciences, University of Guelph, 50 Stone Road East, Guelph, Ontario N1G 2W1, Canada

ARTICLE INFO

Keywords:
Soil texture
Particle size analysis
Image processing
Machine vision
Microscopy
Proximal soil sensing

ABSTRACT

Soil texture (relative proportions of soil particles of varied sizes) is a fundamental soil physical property affecting almost all other soil physical properties and processes of agricultural, environmental and engineering importance. However, characterization of particle sizes in the laboratory presents a range of challenges in terms of the time, labor, difficulty and/or cost involved with the analysis. Continuous wavelet transform (CWT) has been used in characterizing scale-specific variations in spatial or temporal domain as well as in image analysis. The objective of this study was to develop a CWT-based computer vision algorithm to characterize soil particle sizes from digital images captured with a microscope. A cheap portable microscope with 5 MP camera and maximum magnification of 200× was used to develop an image acquisition system. Three images of air-dried, ground (2 mm) soil samples were captured in laboratory conditions for each soil sample (56 + 67 = 123) collected from two agricultural fields (Field26 and Field86) with highly variable soils. Triplicate in-situ images were also collected from 67 locations from Field86 after scrapping off surface residues. The color images were transferred to grey-scale images and the CWT was performed along the 20 equally-spaced rows and columns. The total area under the average global wavelet spectrum represented the total variation in any image. Two fractions of particle sizes; 'coarse' (diameter between 2.0 mm and 0.05 mm) and 'fine' (diameter < 0.05 mm), respectively, representing sand and sum of silt and clay were calculated based on the area under the curve and compared with lab-measured particle sizes using the hydrometer method. The lab-measured coarse- and fine-fractions showed strong agreement with the predicted (from image) fractions. The regression relationship showed the prediction capability of 87% and 88% for coarse (RMSE 44.7 g kg^{-1}) and fine (RMSE 44.7 g kg^{-1}) fractions, respectively for Field26 samples. A similar prediction was obtained (88% with RMSE 40.2 g kg^{-1} for coarse and 88% with RMSE 40.3 g kg^{-1} for fine) for Field86 samples. The efficiency of the wavelet algorithm shows promise in determining the particle sizes from an image and the portable nature of the image acquisition system results in a good proximal soil sensor. In contrast to the laboratory images, a weak prediction (48% for coarse and 56% for fine) was observed for the images taken in-situ mainly due to the quality of the images as they were affected by various field conditions; this requires further research.

1. Introduction

Soil texture, percent distribution of soil particles of varied sizes (sand, silt and clay), has been used to characterize a range of soil physical properties and processes. For instance, soil texture affects infiltration, water holding capacity and drainage, aeration, susceptibility to erosion, cation exchange capacity, and pH buffering capacity which in turn affects the agri-ecosystem productivity. Soil textural information is also critical for soil test result interpretation and recommendations. Similarly, the foundation of buildings, roads and other infrastructures require a detailed knowledge of the composition and texture of soil. Therefore, proper characterization of soil texture can help make informed management decisions for agri-environmental operations and engineering applications.

Traditional soil textural analysis involves several sample pre-processing steps, including sampling and transporting soil to a laboratory, drying, grinding, sieving and storing of the soil for analysis. The most common laboratory analysis method for soil texture determination is sieving for coarse textured or sandy soils and the hydrometer or pipette method following sedimentation theory for finer soil particles, such as silt and clay (Smith and Mullins, 1991). These methods are laborious (e.g. sieving) and time-consuming (e.g. hydrometer) and often

* Corresponding author.
E-mail address: biswas@uoguelph.ca (A. Biswas).

https://doi.org/10.1016/j.compag.2018.03.019
Received 21 August 2017; Received in revised form 10 March 2018; Accepted 17 March 2018

expensive. With technological advancement, a range of modern methods are gaining popularity in soil science to characterize soil particle size distribution, including X-ray absorption, electrical sensing zone, laser diffractions or single optical sizing (Vitton and Sadler, 1997; Fisher et al., 2017; Clayton et al., 2009). All these methods require sophisticated equipment that may be very expensive, need regular maintenance and often they are suitable for laboratory conditions only. Moreover, these methods often provide inconsistent results for heterogeneous soil samples as compared to homogenous materials, such as quartz or glass beads that are used for calibration (Taubner et al., 2009). Other techniques such as visible-near infrared (vis-NIR) and mid-infrared spectroscopy have shown potential in characterizing soil textures quickly (Dhawale, 2015; Vendrame et al., 2012; Zhang et al., 2017). They can classify soil into light, medium or heavy, but cannot provide any further details on soil textural classes (Mouazen et al., 2007). Moreover, these methods require a suitable empirical calibration (possibly site specific) and suffers from issues with in-situ measurements (e.g. presence of water and other environmental conditions). Sensors, such as ground penetration radar (GPR), has been used to collect *in situ* soil measurements (Catakli et al., 2012). However, application of these techniques for large scale field surveys require ancillary knowledge or training and tend to be extremely labor-intensive.

The steady advancement of computational power and development of image acquisition (e.g. cameras) systems, computer vision-based image analysis techniques have received great attention in many fields. For instance, the size of the soil particles could be computed directly from the picture after matching textural patterns (Tuceryan and Jain, 1998). An earlier attempt has been made to characterize soil particle sizes using computer vision algorithms by Ghalib and Hryciw (1999) and Raschke and Hryciw, 1997. A CCD camera was used to capture images of soil samples placed on a platform and illuminated with light from underneath. However, the specificity in the experimental set up restricts its use for *in situ* data collection. Moreover, site-specific calibration was necessary for different landscapes and a better predictive relationship was possible for soils with very limited variability in soil texture within the landscape. With technological advancement, microscope cameras are becoming cheap and portable. The high optical zooms in these microscopes enable the observation of soil fractions in detail. As these cameras provide direct information on soil particle sizes, they show an enormous potential to be used as a proximal soil sensor (that can be used to measure the properties of soils when they are placed in contact with or at a relatively short distance generally under 2 m) provided the images are processed with the right algorithms.

A digital image is a numerical representation of the information content presented through a fixed number of rows and columns of pixels. An individual element of an image is a value representing brightness of a given color. An object in an image is identified as similar value pixels adjacent to each other (in the direction of rows and/or columns). Therefore, any variation in pixel values indicate variability within an image. The variations due to equivalent size particles can be categorized together. Therefore, different sized soil particles will show variations at different separation distances and these distances can be represented as the scales of variations within that image. In a recent study, the authors of this manuscript examined the capability of a computer vision algorithm and digital image processing to quantify soil organic matter and soil texture (Sudarsan et al., 2016). The authors used geostatistical and regression-based methods to analyze the microscope images and developed a relationship between image parameters and soil organic matter and soil texture.

Different mathematical approaches, such as spectral analysis or spectral analysis-based methods, can identify the scales of variations by converting spatial information into scale information. Wavelet based spectral analysis methods were largely successful in identifying scales of variations in spatial or temporal series and show promise in quantifying variations in an image of soil particles and in characterizing soil texture. Principally, wavelet analysis divides a spatial/temporal series into different segments or frequency components and studies each component by comparing a finite scalable window, known as the wavelet. The variations are quantified by shifting the mother wavelet along the spatial series and comparing similarities and dissimilarities.

Wavelet analysis has gained popularity over the last few decades in a variety of fields, including seismic signal detection, atmospheric turbulence, image processing, optics, data compression, simulation, quantum mechanics, soil science and geophysics (Biswas et al., 2008; Biswas and Si, 2011; Biswas, 2014; Biswas, 2018; Kumar and Foufoula-Georgiou, 1997). There are two types of wavelet transforms, namely continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT) (Graps, 1995). A CWT generates information at continuous scales by interpolating between them while DWT is a judicious sub sampling the CWT with twofold (dyadic) increments on the scale (Percival and Walden, 2006). Both methods have their advantages and disadvantages and are suitable for specific applications, while CWT was shown to be more effective in characterizing continuous scales of variations (Biswas and Si, 2011; Lau and Weng, 1995). Therefore, the objective of this study was to evaluate a CWT-based computer vision algorithm to characterize and quantify soil particle size fractions from the digital images captured with a compact microscope-based image acquisition system.

2. Materials and methods

2.1. Instrumentation and hardware

An AD-7013MT USB digital microscope (Dino-Lite Inc., Taipei city, Taiwan) was used to develop an image acquisition system (Fig. 1). The microscope was chosen for its low cost, compact-size and large optical magnification (200×) at 5 MP resolution. A Teflon® holder with a press-fitted scratch resistant fused silica viewing window was constructed to provide a robust platform for operating in field conditions. The microscope was enabled with seven light-emitting diodes (LEDs) for uniform illumination of viewed soil samples and the viewing window allowed maintaining constant distance to the focused-on exposed soil surface. MATLAB (The MathWorks, Inc., Natrick, MA, USA. Release: 2013a) was used to control the image acquisition process (both imaging and LED exposure). The intensity of the LEDs was set to 75% of its capacity to avoid overheating the microscope while maintaining adequate image brightness. Studies with Munsell color using Konica Minolta spectrophotometer showed that controlled lighting conditions were necessary for estimating parameters based on color (Gómez-Robledo et al., 2013). In the current study, these issues were resolved by using the artificial light source (LED) and contact probe (microscope holder allowed contact with soil).

2.2. Site description

An experiment was conducted in two agricultural fields, Field26 (~11 ha) and Field86 (~17 ha) that are located at the Macdonald Campus research farm of McGill University, Ste-Anne-de-Bellevue, Quebec, Canada (45°24′N, 73°56′W). Both fields exhibited high spatial variability in soil types, including both organic and mineral soils and texture varying from sand to clay loam (Fig. 2). Field26 was sampled during the summer of 2014. Presence of considerable number of soil series including Muck (organic soil), St. Zotique, Soulanges, Chicot, Upland, St. Damase, Farmington and Chateauguay series soils (classified following Canadian System of Soil Classification) indicated strong variability in soil types. Field86 was sampled in 2015 and had several soil series within the field including: Chicot, Dalhousie, St-Bernard, Macdonald, St-Amable, Ste-Rosalie and Courval series. Both fields were under minimum-tillage and corn-soybean-forage rotation with sampling being done between soybean and corn crops in both fields.