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Soil Roughness Estimation Using Fractal Analysis on Digital Images of Soil Surface

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Abstract

Irregularities of soil are defined by the term soil surface roughness and various factors affect it such as tillage operations, land management, soil texture, etc. Soil roughness impacts water infiltration and surface storage level, as well as wind and water erosion. We used two classical methods for soil roughness estimation based on chain and pinboard and tested their effectiveness in lab and *in situ* measurements. However, we concluded that even though these two methods are perfectly correlated when they are aligned on the same line over the sample surface, in-field results showed the opposite. Thus, we propose a new soil surface roughness measurement method based on fractal analysis of digital images of the soil surface, acquired using a *camera obscura*-based technique. We show that the 2D fractal analysis gives more pertinent results compared to the other methods designed for 1D measurements.

1 Introduction

Irregularities of soil are defined by the term soil surface roughness (SSR) and it is caused by many factors such as tillage operations, land management, soil texture, etc, and it affects infiltration, surface storage level, wind, and water erosion [1], [2]. SSR is a broad term often referred to as soil microrelief that can be divided into individual indices that describe different characteristics of the soil. One of them and the focus of this study is random roughness (RR) which is related to soil aggregate stability. The term was first used by Burwell et al. (1963) [3] to describe the elevation variations at random points on the soil surface. In comparison, another index that is part of SSR is oriented roughness which describes roughness caused by tillage tool marks and wheel tracks [4].

Various methods have been proposed and used in the last few decades to measure random roughness. They can be divided into two main categories: contact methods; sensor methods. Two contact methods are widely adopted namely pinboard [5] and chain methods [6]. Sensor methods are stereophotogrammetry [7], terrestrial laser scanning [8], and adaptive depth detection by using Xtion Pro by Asus [9]. Thomsen et. al (2015) [10] applied all the mentioned methods to different management and compared the results. Due to the fact that the soil surface is randomly rough, fractal analysis could be used to assess the soil roughness. In [11] some methods are indicated to be using fractal parameters for the evaluation of soil roughness complexity. Consequently, in this article, we make the hypothesis that the fractal analysis is the most appropriate way to assess the soil roughness, due to its application of 2D signals, as opposed to the classical methods (chain and pinboard) focused on line (1D) measurements.

In 1983 Mandelbrot introduced fractal geometry to describe self-similar sets that are referred to as fractals [12]. A measure for characterizing the irregularity and the complexity of a fractal is called fractal dimension (FD) and it indicates how much space is filled. The theoretical Hausdorff fractal dimension is defined for continuous objects, thus not used in practice. Various FD estimators exist, allowing the fractal analysis of digital images exhibiting properties of self-similarity: the probability measure [13, 14], the Minkowski–Bouligand dimension, also known as the box-counting dimension [15], the δ-parallel body method also known as covering-blanket approach, morphological covers or Minkowski sausage [16].

The FD is often used in analyzing structures such as textures that manifest fractal properties in order to discriminate them [17], [18]. In this study, we propose the fractal analysis-based method to estimate RR and compare its performance with two classical methods: the chain and the pin-board method. The methodology is described in Section II while image acquisition and pre-processing are described in Section III. The experimental results are presented in Section IV, along with a comparison. Finally, conclusions are provided in Section V.

2 Methodology

For the experiments, we used the chain method along with our own built pinboard. For the fractal analysis (FA), we designed a camera obscura type of wooden box with a fixed aperture for the camera lens, equipped with LED strips for controlled illumination. Furthermore, we used various artificial surfaces for in lab experiments validation. Afterward, we conducted in situ measurements in an experimental field which is part of the National Institute of Research and Development for Potato and Sugar Beet, Brasov, Romania.

2.1 Chain Method

We employed a bicycle chain in our experiments that have $1m$ length and link pitch equal to 13 mm. RR is defined by a chain roughness (CR) [6] and it is calculated as : $Cr = \left(1 - \frac{L_2}{L_1}\right) \times 100$, where, L_1 - is the size of the chain (1 m) and L_2 - is the Euclidean distance measured by a ruler over the sample surface (m).

2.2 Pinboard Method

Pinboard is a widely-adopted method to measure the RR index and roughness is defined by [5] as the natural logarithm of the standard deviation (SD) of multiple height measurements after eliminating the possible bias (like slope and oriented roughness, or the 10% of upper and lower extreme values). However, later Cremers et. al (1996) [19] proposed that SD of height measurements after eliminating the slope effects is sufficient for the measurements and we adopted this definition of RR. We developed a pinboard setup and it is able to cover the frame with a $73cm$ width. The setup accommodates a total of 53 aluminum pins with $33cm$ height per each, pins are placed with a $10mm$ distance between them and a $3mm$ diameter. Canon 5D Mark II was used for data acquisition. Figure 1 shows the pinboard setup.

2.3 Fractal Analysis

For the experiments we used the approach proposed in [20] adapted to work on 2D (gray-scale image) and 1D signals. We applied the FA on $2D$ gray-scale digital images, size of 256×256 pixels, of soil surface acquired in situ, as well as on the $1D$ average profile (AP), size of 1×256, computed for each digital image. AP was computed as the average of the image lines: $AP = \frac{1}{N}\sum_{i=1}^{N} l_i$, where, l_i - is the ith line of each image. The reason

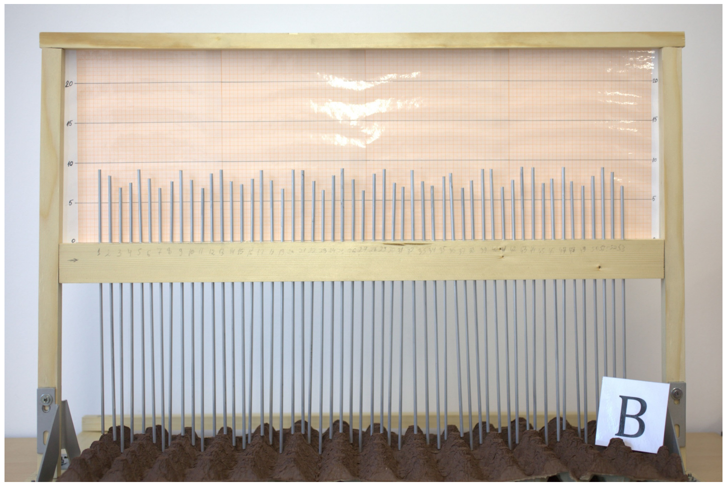
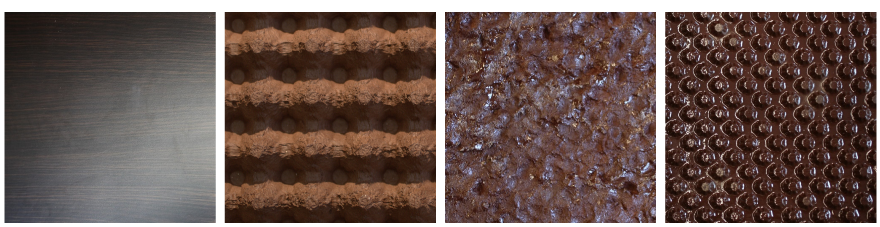


Figure 1: Pinboard in-lab setup.

for computing the AP is based on the experiments presented in [11] where they used a sliding pinboard and averaged the measurements for increased correlation with the other methods.

2.4 Preliminary In-Lab Experiments

We performed several in-lab experiments to validate the tools. Figure 2 shows four artificial surfaces, regular (d), cvasi-regular (b), and irregular (c), that emulate the soil surface of different roughness.



(a) Sample A (b) Sample B (c) Sample C (d) Sample D

Figure 2: Various artificial samples for in lab experiments.

Sample A is a flat surface that we used to compute the mean error of the pinboard, which resulted to be approximately 1 mm. Table 1 displays the SD and CR values for each artificial sample (two measurements were performed for sample B due to its different longitudinal variations).

Table 1: SD and CR of artificial surface samples

Name	Sample A	Sample B	Sample C	Sample D
CR	0	25.29 (16.52)	2.44	6.57
CR*	0	15.03 (13.91)	2.1	7.5
SD	0.094	1.01 (0.92)	0.35	0.27
SD*	0.094	0.52 (0.58)	0.29	0.31

* indicates that the measurements were performed exactly on the same line on the surface. The SD and CR measurements correlate very well both when performed on the same line or not, i.e. a correlation coefficient of 0.93 (0.91 respectively) for the in-lab measurements.

3 Image Acquisition and Pre-processing

Illumination conditions have a significant impact on in situ image acquisition, because the position of the sun during the day may cast shadows that vary as a function of the sun's azimuth angle. Consequently, we developed an acquisition setup based on a black box that contains LED strips for controlled illumination. Figure 3 shows a diagram of the acquisition setup. We used a Canon 5D Mark II digital camera with 21 megapixels for image acquisition. A total of 12 in situ measurements were taken.

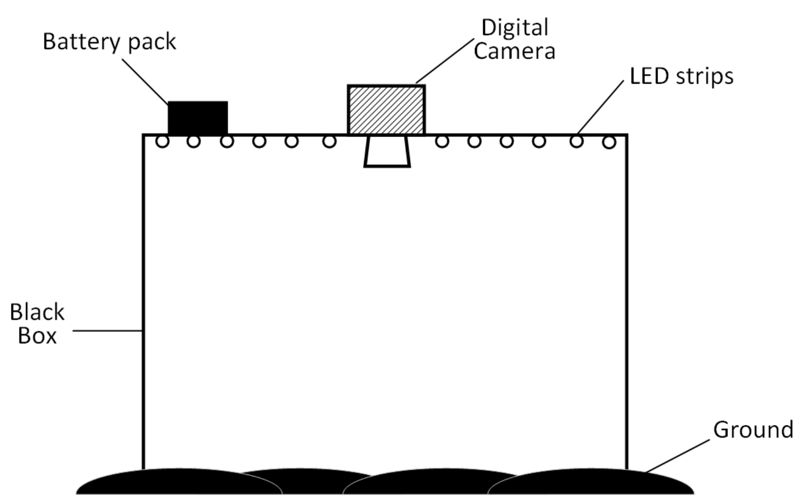


Figure 3: Block diagram of the box setup for fractal analysis.

The black box-based setup is able to completely eliminate sunlight from the surface and LED strips provide constant illumination in order to capture quasi identical-exposure images.

In order to apply FA on acquired images, we preprocessed the images as follows: RGB color images were converted to grayscale to discard the color information which is not relevant to the analysis; we cropped each image creating 7 imagettes / square crops; each image was resized to 256×256. Image brightness was equalized for all images. Considering that we captured 12 color images during in situ measurements, a total of 84 images were obtained after the preprocessing. The purpose of making additional crops is to improve the correlation analysis. Figure 4 shows 12 representative preprocessed images for the 12 locations of in situ image acquisition.

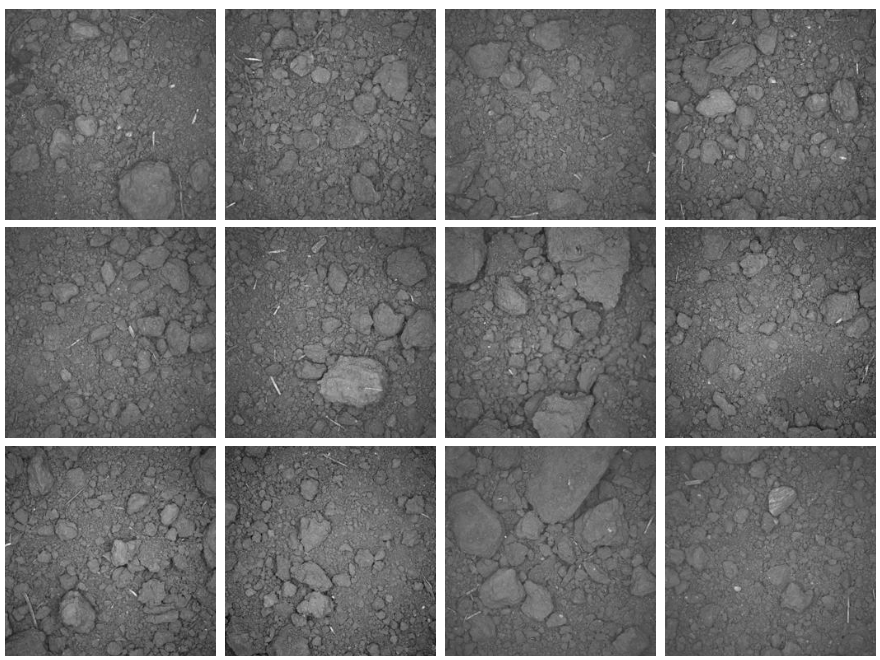
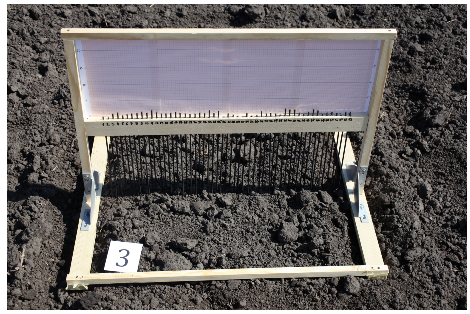


Figure 4: Pre-processed imagettes of soil surfaces for fractal analysis that were taken at 12 different locations.

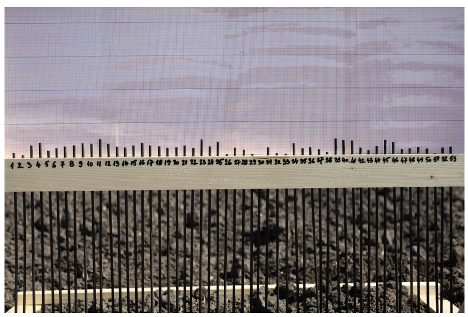
4 Experimental Results

The in-situ usage of chain and pinboard is displayed in Figure 5 along with the location of the measurements.

(a) In situ usage of chain



(b) In situ usage of pinboard



(c) In situ usage of pinboard (detail)

(d) In situ measurement locations

Figure 5: In situ chain and pinboard measurements and locations.

We performed a regression analysis and computed the Pearson correlation coefficient (CC) for the in situ measurements, for the reference methods (chain and pinboard), and for the fractal analysis of image crops. Table 2 shows the CC values between the results of different measurement methods. The in-lab measurements using the reference methods were highly correlated, however, the results in Table 2 demonstrate that in practice, the two reference methods show no correlation at all, as a consequence of the fact that the chain and pinboard measurements were not performed exactly on the same line on the ground. In addition, both methods are slightly intrusive. The correlation between reference methods and fractal analysis is at its best 0.34.

In Figure 6 we show the data and the regression line for the pinboard measurements and the FD of the 84 imagettes representing soil surface digital images (top) and the chain measurements and the FD of the AP of the 12 images corresponding to the 12 measurement locations (bottom).

The fractal analysis shows that the in situ measurements exhibit basically no significant correlation. The reasons may be multiple: the in-situ

Table 2: Correlation analysis results

Regression	**CC**
CR (chain) and SD (pinboard) in situ	-0.09
CR (chain) and SD (imagettes)	0.15
SD (pinboard) and SD (imagettes)	0.21
SD (pinboard) and FD (imagettes)	0.34
CR (chain) and FD (AP)	0.33
SD (pinboard) and FD (AP)	-0.33

classical methods do not correlate either; the performed analysis requires more data for statistical significance; measuring the soil roughness on a line or on a surface makes a significant difference. In Figure 7 we plot two lines (lines $50th$ and $200th$) from one soil surface digital images in Figure 4 and compare them against the AP of the entire image. The two lines have different profiles though the image was captured from a small surface. In [11], the authors used a sliding pinboard then they averaged the measurements, but the AP in Figure 7 exhibits completely different variations (thus complexity) compared to the image lines. Thus averaging the multiple pinboard measurement on a certain area clearly leads to an underestimation of soil characteristics (clearly indicated by both the SD and 1D FA presented in Table 3).

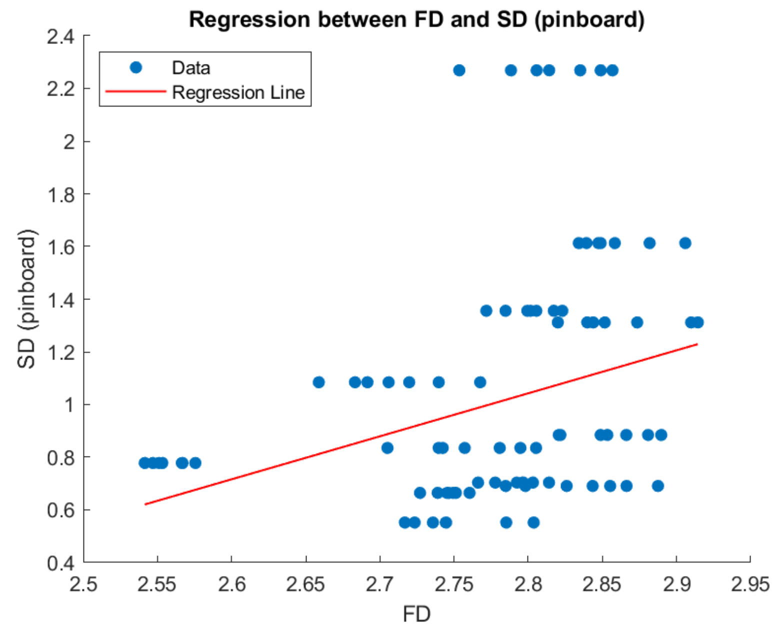
Table 3: 1D FD and SD of selected lines and AP.

	line 50	line 200	AP
SD	18.36	15.59	6.71
FD	1.63	1.8	1.02

5 Conclusions

RR in the context of soil surface roughness is an important parameter in the estimation of soil characteristics. However, the classical (reference) methods do not provide consistent results when used in situ. The correlation analysis shows that in practice the two methods may not provide reliable indications of the RR, as their outcome strongly depends on the position on the ground. In addition, the reference methods are defined for 1D measurements on a single line on the ground, unable to capture the surface variations in

2D. Averaging multiple measurements over a certain area clearly leads to underestimation of the soil roughness. We proposed a new approach to predict RR based on fractal analysis of digital images representing the soil surface acquired in situ in a controlled environment. We showed the results of the correlation analysis between the performed measurements and, as future work, we plan to demonstrate that the $2D$ FA performed on images should be more relevant for soil roughness estimation compared to any type of $1D$ measurements.



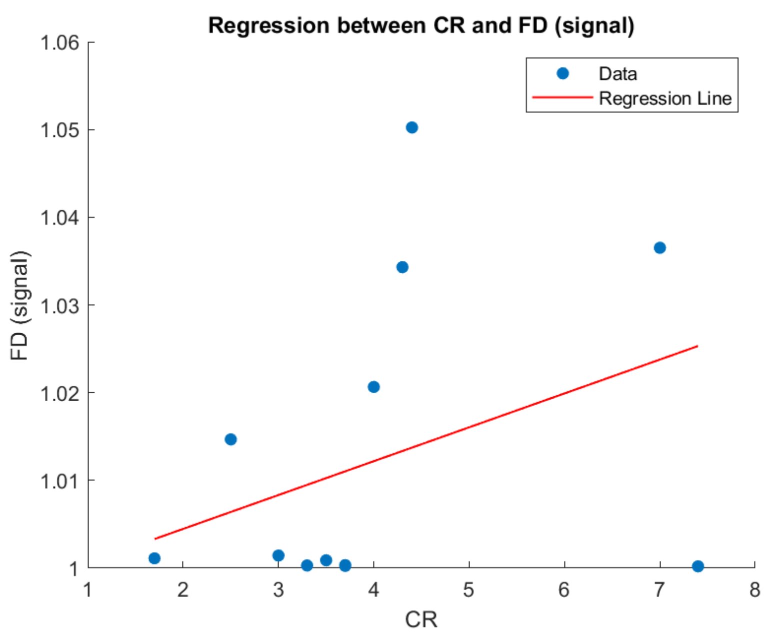


Figure 6: Correlation analysis for pinboard and FD of 84 image crops of soil surface digital images (CC=0.34) and chain and FD of 12 image APs (CC=0.33).

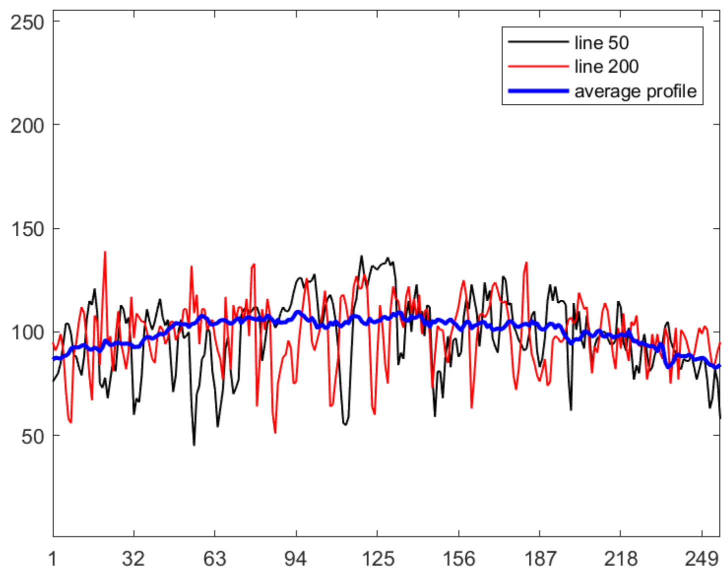


Figure 7: Comparison graph of selected 2 lines and AP of entire image.

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