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A NEW APPROACH FOR ROUGHNESS ANALYSIS OF SOIL SURFACES

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ABSTRACT

We propose a new method for roughness analysis of soil surfaces based on a multiscale approach. Tilled surfaces are decomposed into a large scale oriented structure due to the tillage practice and a non-orderly spatial distribution of clods. The multiresolution approximations of the soil surface allow to characterize these two components. The approximation at the level 4 enhances the large scale oriented structure due to the tillage practice. The spatial distribution of the size of the clods is modeled after the detection of the clods by a dedicated algorithm.
The discrimination between different types of soil tillage practices and the evolution of a soil surface under controlled rainfalls are considered.
The method can be applied to other types of natural relief studies.

1. INTRODUCTION

Soil roughness is a major parameter in remote sensing studies as well as in soil science. It is an entry of physical models used to study soil moisture, soil fertility or erosion phenomena. Roughness of a soil surface is generally estimated with the mean standard deviation of the surface elevations [1,2].
In the industrial domain, the quality of a surface is classically evaluated by separating the form, the waviness and the roughness [3]. These components can be obtained by filtering to enhance the low, middle or high frequencies respectively. Multiresolution analysis is more exhaustive and allows a better characterization of the surface than determining these three components [4].
Soil surfaces are quite different from industrial surfaces (figure 1) and there is a real miss for soil modeling in soil science or in remote sensing. A mere observation of the DEMs clearly shows that the tilled soils surfaces can be seen as the superposition of a large-scale oriented structure due to the soil tillage and a non-orderly spatial distribution of clods of various size on the surface. Consequently, a multiscale analysis appears to be appropriated. We thus propose a method for roughness analysis of tilled soil surfaces based on the characterization of both the large-scale structure and the clods structure. A definition for a soil clod is proposed. The method can be applied to other types of natural relief studies.

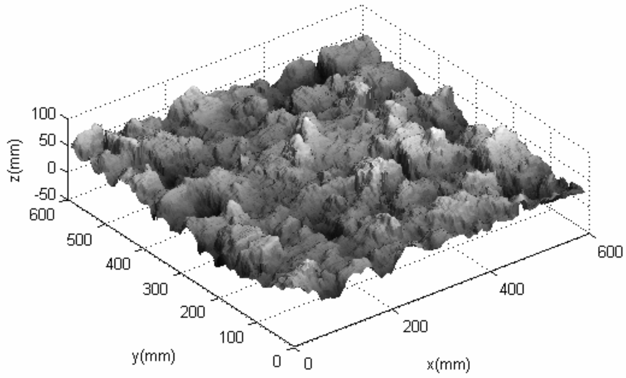

Figure 1: Surface of a seedbed

2. MATERIAL AND METHOD

2.1 Soil surfaces

The data sets used for the present study were collected by stereo-photogrammetry on three different kinds of tilled soils: seedbed, chisel ploughing and conventional ploughing. The horizontal dimensions of the retrieved Digital Elevation Models (DEMs) used for the present study are 60 x 60 cm^2. The resolution is 1 mm in both horizontal directions and 2 mm in the vertical direction. For each tillage practice, two plots were selected and the DEMs for this initial state were subsequently recorded. Then artificial rainfalls were used to get for each spot two extra DEMs corresponding to two different stages of the controlled evolution of the soil. The complete protocol of watering and DEM reconstitution is described in [5].

2.2 Multiresolution analysis

The theory of wavelet-based multiresolution analysis for signals and images was introduced by Mallat [6]. Assuming the fact, that the soil-air interface can be modeled by the DEM $z=S(x,y)$ function, it is possible to decompose the surface at different levels N, into one approximation $A_N(x,y)$ and the sum of N details $D_1(x,y)$, …, $D_N(x,y)$:

$$S(x,y) = A_N(x,y) + \sum_{n=1}^{N} D_n(x,y)$$

This decomposition relies on the use of an orthogonal wavelet family that must be chosen according to the specificity of the application.

For $n = 0$, the approximation is the DEM itself and no detail is introduced:

$$S(x,y) = A_0(x,y)$$

Successive approximations and related details are calculated at each intermediate level n according to the recursion:

$$A_{n-1}(x,y) = A_n(x,y) + D_n(x,y).$$

$A_n(x,y)$ and $D_n(x,y)$ are obtained by filtering and down sampling as illustrated on the figure 2. $D_n(x,y)$ denotes the sum of the three detail surfaces delivered by the filters :

$$D_n(x,y) = D_{Hn}(x,y) + D_{Vn}(x,y) + D_{Dn}(x,y).$$

Taking the approximation $A_N(x,y)$ of $S(x,y)$ at increasing levels N leads to smoother and smoother surfaces.

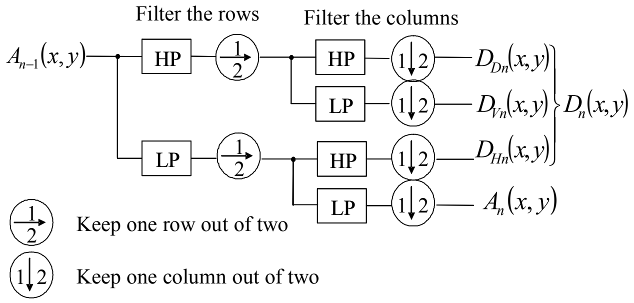

Figure 2: Step of the recursion giving the approximation and the detail at the level n

HP stands for the high pass filter associated to the wavelet and LP for the low pass filter associated to the corresponding scaling function.

2.3 Algorithm for the detection of the clods

Retrieving the clods structure enables to complete the statistical characterization of the soil surface roughness. The concept of clod is not very clear in soil science. The more intuitive definition is a heap of earth. We introduce a more quantified definition with this algorithm of detection. We suppose that the clods of small diameters are enhanced at a fine resolution and then disappear at a coarser resolution, where large clods will be enhanced. A complex relief with superposition of bumps can thus be analyzed at different resolutions.

The algorithm for the detection of the clods is illustrated on the figure 3. The detection is performed for each surface approximation and then the detected clods are merged from coarse to fine resolutions.

Considering a surface approximation, the likely clods are first localized by searching for the local maxima. This procedure is made in two steps:

- a moving window captures a great number of maxima; the size of the window is fixed to 5 (mm) according to the minimum diameter of the clod to be detected.
- border effects are corrected by comparing the maxima to their neighbours.

1) Detect the clods on the approximations

For each surface approximation :

Detect the local maxima of the surface with a moving window

For each maximum :

Make an estimation of the clod border in the directions x and y by looking for a change of the slope

Check for the change in altitude to discard flat bumps and sharp peaks

2) Merge the detections at the different resolutions from coarse to fine

Figure 3: algorithm for the detection of the clods

Once the maxima are retrieved, the extensions of the likely clods in both x and y directions are estimated with the slope variation of z. The border is approximately at the point where the slope is horizontal. Asymmetric extensions are penalized. Finally, the detection of the clod is validated with a test on the change in altitude between its summit and its borders. This extra test makes a compromise between flatness and sharpness, thus discarding unrealistic clods.

2.4 Discrimination between the tillage practices

The benefit of the multiresolution approach was quantified by studying the discrimination between the tillage practices. The discrimination potential of a variable v can be evaluated using the between over total dispersion ratio I_b/I_t [7].

Generally, the whole data set B is partitioned into k groups composed of respectively n_1, ... n_k surfaces, $\bar{v}$ denotes the mean of v computed over B, $\bar{v}_h$ is the mean of v over the group h, and v_{hi} is the value of v for the i^{th} surface of the group h. The between dispersion is defined as:

$$I_b = \sum_{h=1}^{k} n_h (\bar{v}_h - \bar{v})^2 .$$

It represents the distance between the centers of the groups. The within dispersion:

$$I_w = \sum_{h=1}^{k} \sum_{i=1}^{n_h} (v_{hi} - \bar{v}_h)^2$$

represents the compactness of the groups.

The total dispersion:

$$I_t = I_w + I_b = \sum_{h=1}^{k} \sum_{i=1}^{n_h} (v_{hi} - \bar{v})^2$$

represents the spread of the data cloud. The ratio I_b/I_t takes its values between 0 and 1. The higher this ratio is, the better the discrimination between groups can be.

The data base available for our study was made of $k = 3$ types of tillage practice, and $n_1 = n_2 = n_3 = 6$ surfaces per tillage practice. The variable v was the standard deviation of the elevations. The results are presented in the next section.

3. RESULTS

3.1 Roughness analysis with the standard deviation of the elevations

The parameter most commonly used to characterize the soil roughness in soil science or in remote sensing is the mean standard deviation of the surface elevations. It corresponds also to the root mean square *rms*. As the soil tillage induces a not isotropic behaviour of the roughness, the parameter *rms* was calculated along and across the furrows for the different surfaces of our data set. It was calculated on the original surfaces and on selected approximations. It was then denoted rms_{Ai}.
The means obtained for the original surfaces of the three kinds of tillage practices are presented in table 1. The parameter *rms* across the furrows had the best discrimination potential. It gave a dispersion ratio I_b/I_t = 81.3 %.

	Seed bed	Chisel p.	Conventional p.	I_b/I_t (%)
rms along the furrows (mm)	13.5	14.9	19.08	72.0
rms across the furrows (mm)	13.53	21.33	26.55	81.3

Table 1: Mean standard deviations of the elevations

To make the calculation on the approximation surfaces, a wavelet family and a level of decomposition were first chosen. The mean standard deviation of the elevations was also used to determine how close an approximation to the original surface is. The choice of a wavelet family was made for each kind of tillage practice in order to maximize the ratio rms_{An}/rms. The best results are summarized in table 2. They were obtained with the wavelets “db9” for seedbeds, “sym9” for chisel ploughings and “sym10” for conventional ploughings. The maximum level of decomposition was limited to $N = 4$, because at greater levels, the approximation was no more meaningful for seedbeds surfaces. Level 5 was possible to use for chisel ploughings and conventional ploughings surfaces, which are composed of larger scale structures.

	A_1	A_2	A_3	A_4
Seedbed	99.9 %	99.7 %	99.2 %	97.2 %
Chisel ploughing	99.9 %	99.75 %	99.3 %	97.8 %
Conventional ploughing	99.9 %	99.7 %	99.4 %	98.1 %

Table 2: rms_{An}/rms ratio with the level of decomposition

A_1 and A_2 are very close to *S* because of possible over sampling of the data. A_4 is still close to *S* on account to the smoothness of a soil’s surface. Level 4 was the one that presented the best discrimination potential with a dispersion ratio I_b/I_t = 89.6 %. This ratio was obtained with the wavelet transform coefficients, thus enhancing the dispersion ratio obtained on the original surfaces.

3.2 Roughness analysis with the detection of the clods

The clods were detected using A_2, A_3 and A_4 for seedbeds surfaces and adding A_5 for chisel ploughings and conventional ploughings surfaces. A_1 was not used because it was not smooth enough to allow reliable border estimation for the clods. More or less 200 clods were detected for each surface. An example of detection is illustrated on the figure 4. Each clod is marked by its summit and its extensions in the horizontal directions. Some relieves are composed of several bumps considered as clods. The definition of a clod may be revised when the concept of clod will be clearer in soil science.

Figure 4: Detection of the clods for a portion of a seedbed’s surface

Once the clods are detected, it is possible to make statistics on the clods characteristics. In this study, we focused on the area *a* calculated with the horizontal extensions of the clods. A comparison between four probability density functions (pdf): lognormal, Beta, exponential and Gamma was performed by comparing the area *a* of the detected clods and the area predicted by the probability model. Data were normalized to take values between 0 and 1 for the comparison. Gamma pdf appeared as the best model for the three types of soil practice surfaces. It has two parameters *p* and λ and can be written as:

$$f(a) = \frac{\lambda}{\Gamma(p)} e^{-\lambda a} (\lambda a)^{p-1}.$$

The Gamma function is defined as

$$\Gamma(x) = \int_0^{\infty} t^{x-1} e^{-t} dt.$$

The mean deviation between measured normalized areas and predicted areas was 10^{-3}. The figure 5 shows the evolution of the parameters of the Gamma pdf as the soils are degraded with controlled rainfalls. The seedbeds are quite separated from the other soils because seeding leads to smaller structures. Chisel and ploughing are closer practices, which can explain the same behaviour when studying the distribution of the size of the clods.
The parameter p tends toward 1 as the soils are degraded for the three practices. In fact, a Gamma pdf with parameter p = 1 is equivalent to an exponential pdf of parameter λ. Therefore, the evolution of the soil surface under rainfalls tends to simplify the probability model of the distribution of the clods.

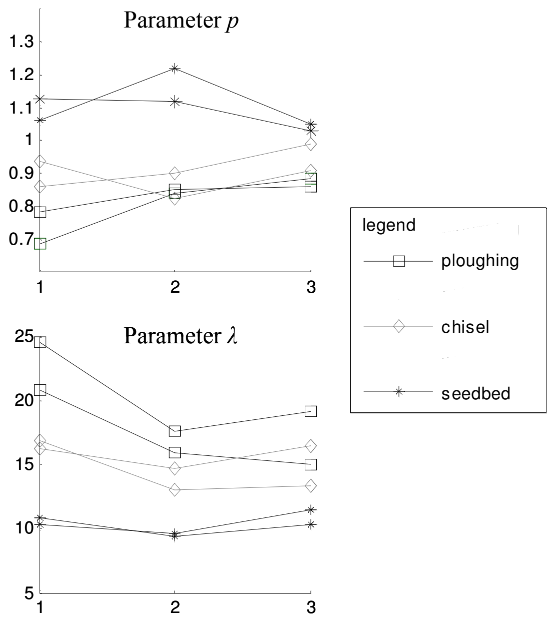

Figure 5: Evolution of the distributions of the clods under rainfalls

States of evolution of the surface : 1) original 2) after one rainfall 3) after two rainfalls

4. CONCLUSION

We proposed a new method for roughness analysis of soil surfaces. Tilled surfaces can be seen as the superposition of a large scale oriented structure due to the tillage practice and a non-orderly spatial distribution of clods. The multiresolution approximations of the soil surface allow characterizing these two components. The mean standard deviation of the surface approximation wavelet coefficients at the level 4 had a good potential to discriminate between the tillage practices with a dispersion ratio of 89.6 %. This ratio was only of 81.3 % when calculated on the elevations of original surfaces. Therefore, the approximation at the level 4 enhances the large scale oriented structure due to the tillage practice and captures most of the surface features.

The spatial distribution of the size of the clods was modeled by a gamma pdf after the detection of the clods by a dedicated algorithm. The detection was performed for each surface approximation and then the clods were merged from coarse to fine resolutions. There was little difference between the pdf of the size of the clods for the three types of tillage practices. The larger difference occurred between seedbeds and the two other types of soils. The evolution of the soils under rainfalls seems to be the same for the three types of tillage practices and tends to a simplification of the pdf model.

The difference between soil surfaces seems to rely more on the oriented structure than on the spatial distribution of the clods. Nevertheless, it would be possible to define other statistical parameters in order to enhance the difference between the spatial distributions of the clods. For example, the maximum size of the clods or the percentage of one size class over the whole classes could be interesting parameters.

This method was developed for tilled soil surfaces; it can be applied to other types of natural relief studies. It has the advantage of a multiresolution approach, offering both a global characterization of a surface and local and precise information on the position of the clods or other small relieves.

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