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Automatic clod detection and boundary estimation from Digital Elevation Model images using different approaches

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ABSTRACT

Soil micro-topography characterization is an important issue for both soil science and remote sensing data interpretation. The objective of present study is to propose and discuss some methods dedicated to the automatic localization of clods (or big aggregates) on Digital Elevation Model images of soil. Two new image processing methods are introduced. The first one deals with the clod detection and the rough estimation of their boundaries. It is based on the adaptation of a famous segmentation algorithm applied to a modified surface enhancing the main features characterizing the clods. The second proposed method deals with the accurate estimation of clod boundaries. Clod boundaries are moved based on dynamic programming. Both proposed methods are validated on laboratory-built surfaces and on an actual surface recorded in an agricultural field. Results show that the proposed methods outperformed previously published methods.
The proposed processing of DEM images allows the detection of the aggregates and clods deposited on the soil surface and the accurate estimation of their boundaries. The practice is facilitated by the proposition of default values for the parameters. The implications are the automatic analysis of DEM images that is a step towards micro-topography statistical characterization.

1. Introduction

Soil roughness is a key parameter to understand soil properties and physical processes related to energy and mass transfer between the atmosphere and the soil, surface water flow processes, soil erosion and agronomic processes, such as seed germination and seedling emergence. Tillage implements on bare agricultural soils, such as seedbed preparation, lead to low and moderate roughness. The cloddiness can then be quantified in terms of the sizes of the aggregates and clods and their size distribution that are key features of bare soil microrelief to understand two major processes. The first one deals with the choice of optimum tillage to obtain the most favorable plant emergence and the second one is the study of the rainfall impact on microrelief changes. These two processes depend also on other soil physical properties, such as the soil texture, the soil water content and the soil hydraulic properties. Many authors noted that most of the mechanisms of soil fragmentation by tillage implements and of water interaction with the soil surface occur at millimeter scales, (e.g. Arvidsson and Bölenius, 2006; Berntsen and Berre, 2002; Kamphorst et al., 2005; Martin et al., 2008; Roger-Estrade et al., 2004; Rudolph et al., 1997).

In the field of remote sensing, soil roughness at small scale occurs for the analysis and interpretation of measurements both in optical domain (visible and near infra-red) and in active microwave one. Indeed, the bidirectional reflectance and the Synthetic Aperture Radar (SAR) signals are very sensitive to soil surface state, especially soil surface irregularities and structures (clod arrangement, furrows). Soil aggregates and clods produced by farming practices affect the bidirectional reflectance by shadowing effect. They have to be separated from soil radiative properties related to biochemical factors, (e.g. Cierniewski et al., 1996; Wang et al., 2012; Wu et al., 2009). The microwave backscattering coefficient also depends on the local surface slope at centimeter scale, which is directly related to clod arrangements. Then, several studies investigate the sensitivity of SAR radars to soil surface parameters, (e.g. Corbane et al., 2011; Holah et al., 2005; Lievens et al., 2011; Verhoest et al., 2008; Zribi et al., 2000). In order to link the remote sensing data to scattering physical models and for modeling purpose, it is important to further characterize key features of the soil micro-relief.

Two scales are usually considered for soil roughness modeling. Firstly, the surface is globally characterized by its autocorrelation function model and/or by statistical indices, (e.g. Bertuzzi et al., 1990; Dusséaux et al., 2012; Helming et al., 1993; Römkens and Wang, 1986; Taconet and Ciarletti, 2007). Secondly, a more local and detailed analysis of the surface is performed by focusing on patterns such as aggregates, clods and mound-and-depressions (Ambassa-Kiki and Lal, 1992; Arvidsson and Bölenius, 2006; Borselli and Torri, 2010; Darboux et al., 2001; Kamphorst et al., 2005). In this study we call 'support surface' the soil surface model neglecting these aggregates,

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clods and depressions. Several works have already dealt with the problem of clod detection/estimation in the case of an agricultural surface (Jester and Klik, 2005; Vannier et al., 2009). The basic sieving (that allows filtering the clods according to their size) being fastidious, alternative methods have been proposed, such as works based on image processing. Two main kinds of image contents have been considered: visible reflectance images (Sandri et al., 1998; Warner, 1995), providing 2D information, and Digital Elevation Model (DEM) images (Helming et al., 1993), providing 3D information. On the one hand, using visible reflectance images, most classical image processing tools apply. On the other hand, due to the fact that main clod features are geometric, 3D geometric measurements seem much more appropriate than radiometric ones so that several techniques have been developed to acquire DEM images, either based on laser measurements (Bertuzzi et al., 1990; Huang and Bradford, 1990) or on stereovision (Taconet and Ciarletti, 2007). Specifically, stereovision exploits images (photographic or digital) acquired with different view angles to determine the 3D geometry of the scene (in our case, the reconstruction of the surface of the agricultural area in 3D space). Now, when handling images of the surface, the estimation of its physical parameters may be not direct. Then, the first task to study patterns such as clods or aggregates is to delineate them on the image. Indeed from this delineation, some 2D parameters derived from the footprint (such as the mean surface of the aggregates and their spacing) can be computed as well as some 3D parameters (such as the mean volume of the aggregates) if a DEM image is available. For instance, applying their method (Taconet et al., 2010) of automatic clod delineation on DEM images on a large dataset of several hundred of clods, Taconet et al. (2013) shows that these irregular shaped objects can be rather well approximated by simple approached forms (an ellipse for the basis and a half cosine function for the height). In this study we focus on clods or aggregates delineation using DEM images.

Since DEM pixel values represent the altitude, some discriminative clod features may be: (i) the clod pixels have a higher value than support surface pixels around the clods, (ii) the clod contours correspond to 'rapid' variations of pixel values, and (iii) each clod has one main maximum of values. We use the term 'contour' when referring the clod boundary represented in the image domain. Now, in the case of DEM images, classical segmentation methods fail to identify the clods on the support surface, due to the intrinsic non-homogeneity of the clod values (altitudes). Thus, classical image processing tools should be adapted or new ones should be developed. For instance, Taconet et al. (2010) developed a specific level line based approach.

The aim of this study is to provide a comparison between different algorithms for clod detection. The first one is (Taconet et al., 2010) mentioned just above. Its main drawback is the under-estimation of the clod size due to a location of the contours inside the clods. The second one is the extension of a preliminary work (Chimi-Chiadjeu et al., 2012), where we had proposed to adapt the so-called 'watershed' algorithm to our problem of clod detection. The two last ones deal with the improvement of the clod location rather than with their detection. Both are based on clod contour move. The first one (Chimi-Chiadjeu et al., 2013) aims at moving the initial contour using a simulated annealing optimization. Anyway, because of its computational heaviness, it is not adapted to actual surfaces. Then, in this work, we propose a new approach based on dynamic programming that outperforms previous work. In order to provide some quantitative results, we test the different algorithms on data acquired either on laboratory-built surfaces or on an actual surface obtained on an agricultural soil.

2. Image processing methods for clod estimation

In this work we focus on clod detection or estimation using DEM images, that is to say images where the value in every pixel represents the elevation or altitude (z coordinate). Clods are characterized both by altitude features (they are 'above' the support surface) and by slope features (assuming as in Richard et al. (1999) that clods are roughly comparable to half ellipsoids, boils down to assume a high value for the slope around clod boundaries). The different methods for clod detection from DEM images are thus based on these features (altitude and slope), formalized in different ways, depending on the chosen clod model and on the constraints due to the used estimation algorithm.

Let us first define some notations. H is the DEM image, x is the row coordinate, $y \in \{1,\cdots,N_r\}$, and y is the column coordinate, $y \in \{1,\cdots,N_c\}$, so that $H(x, y)$ denotes the altitude value in pixel of image coordinates (x, y). In every pixel, the altitude gradient is a vector with two components respectively along the row and the column directions. Several image processing tools have been proposed to estimate these two components. Simpler techniques are linear filtering, e.g. Sobel operator (Ziou and Tabbone, 1998), whereas 'optimal filtering' has also been proposed, (e.g. Canny, 1986; Deriche, 1987; Haralick, 1984). Although in most cases linear estimation is sufficient, in the following we note $G(x, y)$ the estimate of the gradient norm at pixel (x, y), without specifying the way it has been estimated.

In this study, we distinguish between methods for clod detection (and rough estimation of their contours) that do not require initialization, and methods for improvement of clod contour estimation that require an initialization. In each case, before presenting the proposed approach, we briefly recall the state of the art for the considered problem in order to further evaluate the interest of the proposed approach relatively to it.

2.1. Clod detection and rough estimation of their contours

2.1.1. Background in clod detection

Taconet et al. (2010) proposed an original method mainly based on the analysis of the level lines in the image H. In image processing, a level line is a set of connected pixels having the same value in the image. Thus for DEM images, a closed level line corresponds to an elevation contour. A key point of Taconet's method is the selection of the level lines of interest. Two criteria have been used. First, only the closed level lines of minimum length are considered. In particular, the clods intersecting the image borders (i.e. the clods not completely included in the image domain) are not considered. Second, only the level lines with pixels of 'highest' gradient norm values are considered. The word 'highest' refers to a percentile p of the pixels presenting the $pN_r N_c$ higher values in G image. Then, the definition of a clod is as follows: a clod is a concave 2D function (of altitude). In terms of level lines it means that a clod only includes nested level lines. Practically, from selected level lines (both criteria), a clod center is defined as a level line with no other included level line, and a clod contour is defined as the longest level line having only one clod center included. We refer the reader to Taconet et al. (2010) for more detailed information on the practical implementation of the method.

Clod detection proposed by Taconet et al. (2010) is mainly based on altitude information (H image) whereas gradient norm information (G image) is used as a constraint. Altitude information is used without preprocessing (e.g. filtering, contrast enhancement) so that any irregularity in the DEM image has an impact on clod detection. In particular, when a clod has several summits (even very slightly pronounced) it is divided in as many detections. Another drawback of the method is that searching the clod contour among the (selected) level lines, the clod basis can only be horizontal whereas, actually, a clod can stand on a non-horizontal surface (the side of a furrow, for example). To overcome these drawbacks, a new method was investigated.

2.1.2. Proposed method based on watershed segmentation

We propose to split our problem of clod detection (and rough contour estimation) into two sub-problems. The first one deals with the image segmentation into regions so that the clods coincide with some of them. The second one deals with the selection of the