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Automatic quantification of crack patterns by image processing ☆

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ABSTRACT

Image processing technologies are proposed to quantify crack patterns. On the basis of the technologies, a software "Crack Image Analysis System" (CIAS) has been developed. An image of soil crack network is used as an example to illustrate the image processing technologies and the operations of the CIAS. The quantification of the crack image involves the following three steps: image segmentation, crack identification and measurement. First, the image is converted to a binary image using a cluster analysis method; noise in the binary image is removed; and crack spaces are fused. Then, the medial axis of the crack network is extracted from the binary image, with which nodes and crack segments can be identified. Finally, various geometric parameters of the crack network can be calculated automatically, such as node number, crack number, clod area, clod perimeter, crack area, width, length, and direction. The thresholds used in the operations are specified by cluster analysis and other innovative methods. As a result, the objects (nodes, cracks and clods) in the crack network can be quantified automatically. The software may be used to study the generation and development of soil crack patterns and rock fractures.

1. Introduction

Quantitative analysis of crack pattern is an important aspect of the study of cracking behavior of soils and rocks. The shape, size, ruggedness, connectivity and branching of the crack patterns are not only associated with their historical stresses and strains, but also have implications for their future stability and functionality (Preston et al., 1997; Tang et al., 2008). Traditional manual characterization of the crack pattern is associated with low-accuracy, low-efficiency and artificial errors. In certain cases, the original crack pattern can be disturbed by human activities and equipment, which usually results in large measurement errors (Lima and Grismer, 1992; Dasog and Shashidhara, 1993).

Advancement in the computer hardware and software capabilities has made image analysis a new and efficient tool that can be applied to process crack images (Yan et al., 2002). So far, with the aim to investigate the dynamics of crack formation, certain image processing technologies have been introduced to analyze the geometry of cracks. However, crack networks are complex systems, which involve crack segments, nodes, and the clods surrounded by the cracks. Current tools are only limited to the quantification of basic geometric parameters of cracks, such as crack direction (Lakshmikantha et al., 2009), crack shape (Liu et al., 2008), fractal dimension (Baer et al., 2009), etc. The advance in the research of cracking behaviors of materials requires a new tool to quantify crack networks and the geometry of all the objects in crack networks.

In order to quantify the geometry of crack networks, a software "Crack Image Analysis System" (CIAS) has been developed. By using this software, various geometric parameters can also be calculated automatically, such as node- and crack-numbers, clod area, clod perimeter, crack area, width, length, and direction.

2. Image processing of crack image

2.1. Preparation of crack image

In order to illustrate the image processing technologies and the operations of the CIAS, an image of a laboratory soil crack was used as an example. A plate of soil slurry was placed in a dry-oven with constant temperature 40 °C, and the final soil crack pattern is shown in Fig. 1a. Note that the figure represents the central part of the sample, an area which is $120 \times 120\ mm^2$ (1008×1008 pixels) in size. The cracks and the background are distinguished according to their different gray levels. Therefore, the brightness of cracks and background should be quite different. The photos were taken in moderate light condition, and the direction of camera was perpendicular to the crack plane.

2.2. Image segmentation

As shown in Fig. 1b, the two crests in the gray-level histogram of the image represent the cracks and the clods. The global

☆Data and software for the image processing developed in this paper are available online: http://acei.cn/program/CIAS.

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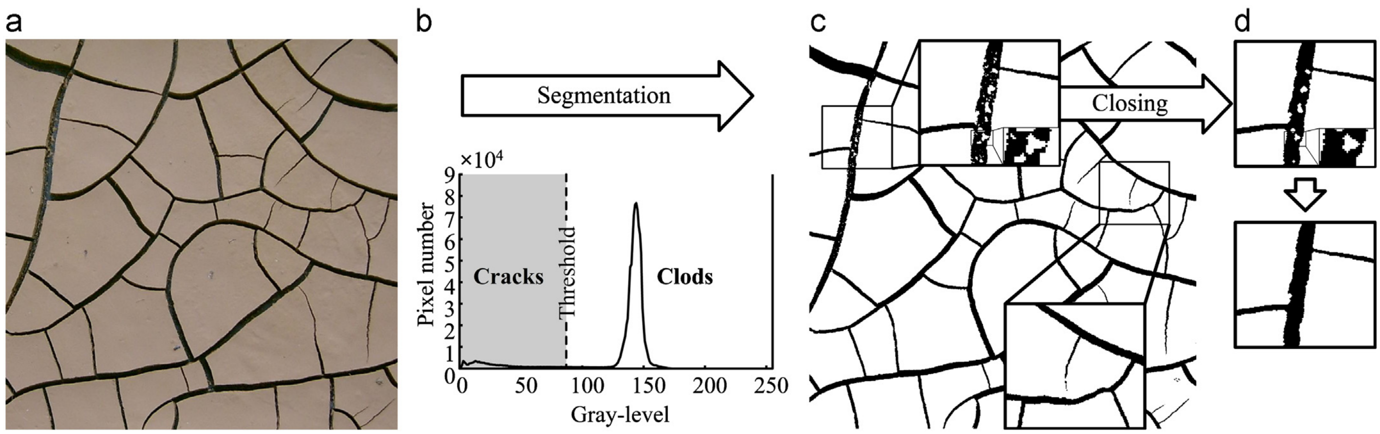

Fig. 1. (a) Original crack image and (b) gray-level histogram and cluster analysis are used to distinguish the cracks and clods. (c) Binary image with white and black spots, bottom right side shows a discontinuous crack, which can be repaired by crack restoration (Fig. 2), and (d) the bridge between spots and real clods are eliminated using Closing, and spots are removed.

threshold to segment the image can be determined using a cluster analysis method: (a) by using a given threshold T, the image can be divided into two pixel sets: the white pixels (W), of which the gray-level is greater than T, and the black pixels (K), which includes the remaining pixels. (b) Let G_W and G_K represent the average gray level of the pixel sets W and K, respectively. The new threshold is defined as the average of G_W and G_K.

The average gray level of the image is used as the initial threshold. Then, repeat steps (a) and (b) until the threshold converges to a constant value, which is the optimal threshold. As shown in Fig. 1b, the optimal threshold is between the two crests in the gray-level histogram, and as a result, the crack network is discriminated from the background automatically (Fig. 1c).

2.3. Spot removal

There are a large number of small spots in the binary image, such as white dots within the cracks and black spots over the clods (Fig. 1c). Isolated white regions (includes clods and spots) were identified using the Seed Filling algorithm (Yu et al., 2010). These dots and spots were then removed according to their different sizes (Liu et al., 2011). Since the black and white spots are much smaller than the cracks and the real clods, the spot threshold can also be specified using the cluster analysis method. The CIAS also provides the traditional Closing operation (Gonzalez and Woods, 2002) to reduce the noise (Fig. 1d).

3. Crack network identification

3.1. Clod identification and crack restoration

In the crack image, the soil block is divided into many small clods, which can be identified using the Seed Filling algorithm (Yu et al., 2010). However, due to undesired image noise, some original continuous fine cracks may become discontinuous in the binary image (bottom-right side of Fig. 1c). As a result, two neighboring clods may connect with each other via the bridge between them.

A clod division method is proposed to divide the clods and to repair the cracks. (1) First, a dilation operation (Gonzalez and Woods, 2002) is applied to the binary image to eliminate the narrow bridge between clods. In this way, the crack space is fused (Fig. 2a–b), since the diameter of the space is smaller than the diameter of the dilation structuring element B. (2) As the space (i.e. bridge) has been eliminated, the two isolated clods (S_1 and S_2 in Fig. 2c) can be identified using the Seed Filling algorithm

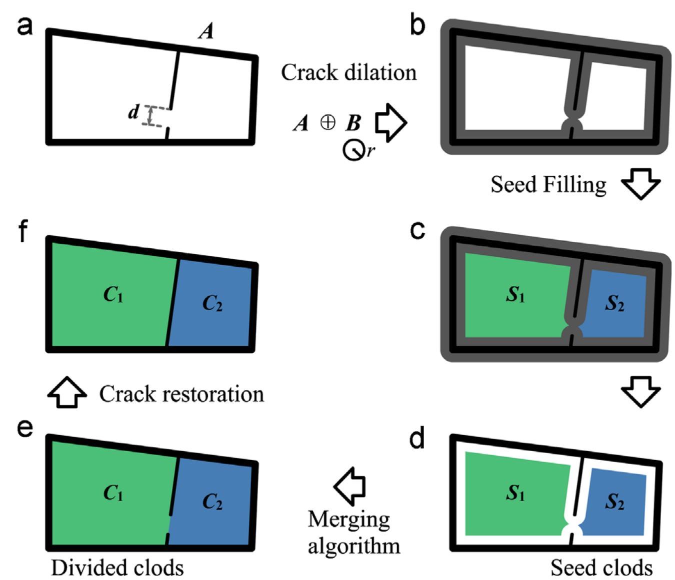

Fig. 2. Schematic diagram of clod division and crack restoration (a) two clods connect with each other via a crack space (see Fig. 1c). (b) The cracks A are dilated by a structuring element B, (c) Seed Filling is used to identify the two isolated regions, S_1 and S_2. (d–e) The white pixels are integrated to nearby seed clods using the Merging algorithm. (f) The crack is repaired along the interface between clods.

(Yu et al., 2010). (3) In Fig. 2d–e, the pixels of the dilated parts are integrated into the seed regions using the Merging algorithm (Liu et al., 2011), and the whole region is then divided into two clods. (4) Finally, the crack is bridged along the interface between clods (Fig. 2f).

3.2. Crack identification

The cracks and nodes can be identified by the following steps:

(1) The one-pixel-width medial axis of the crack network can be extracted by the Skeleton algorithm (Lakshmikantha et al., 2009). However, this procedure tends to leave parasitic branches, which can be cleaned up by Pruning (Fig. 3b; Gonzalez and Woods, 2002). Generally, the length of the parasitic branch is less than the crack width, and therefore the maximum crack width can be used as the default Pruning threshold.

(2) For each medial axis pixel, track its 8-neighbors in clockwise direction. Let N represent the time that pixel color changes