Energy-based binary segmentation of snow microtomographic images

Pascal Hagenmuller[1], Guillaume Chambon[1], Bernard Lesaffre[2], Frederic Flin[2], Neige Calonne[2] and Mohamed Naaim[1]

[1]Irstea, UR ETGR Erosion torrentielle neige et avalanches, Saint-Martin-d'Hères, F-38402, France, [email: pascal.hagenmuller@irstea.fr]

[2]Météo-France - CNRS, CNRM-GAME, CEN, Saint-Martin-d'Hères, F-38400, France

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ABSTRACT

X-ray micro-tomography has become an essential tool to investigate the mechanical and physical properties of snow, which are tied to its microstructure. A crucial step in the 3D image processing is the binary segmentation of the grayscale X-ray attenuation coefficient image to a binary ice/pore image. In the snow community, this step is usually based on global thresholding conducted with smoothing filters. In practice, this standard segmentation method presents drawbacks and often requires time-consuming manual post-processing. We use a segmentation method based on the minimization of an energy function. The energy definition formally expresses the segmentation criteria and clearly defines the effective resolution of the output image. Moreover, the global optimization through graph-cuts is particularly robust. We applied this method to different snow images and we successfully compared the results to standard segmentation techniques. Finally, the segmentation sensibility to the smoothness parameter is analyzed.

1. INTRODUCTION

Natural snow exists very close to its melting point. Thus, once fallen on the ground, snow undergoes metamorphism due to rapid recrystallization. The shape and the arrangement of snow grains are extremely variable because of metamorphism (see Figure 1), and determine most of the mechanical and physical properties of snow. Characterizations of the snow microstructure with bulk variables or variables derived from 2D images of snow are often poor to understand the snow properties (Shapiro 1997). Therefore, acquiring 3D representations of the ice matrix at a scale of a few microns is essential in snow research.

The main technique to image snow samples is X-ray micro-tomography (µCT, e.g. Coléou et al. 2001). To allow quantitative analysis of the snow structure, the X-ray attenuation coefficient image needs to be reduced to a binary ice/pore image. Binary segmentation is a crucial image processing step because it affects all subsequent quantitative analysis and modeling. In snow research, segmentation is usually based on global thresholding combined with smoothing filters. Some studies have pointed out the difficulty to find the best threshold value, especially if the grayscale histogram is uni-modal (e.g. Kerbrat 2008). However few attention was paid to the effect of the binary segmentation algorithm. Iassonov et al. (2009) compared various segmentation techniques and concluded that global thresholding methods yield unsatisfactory segmentation and that the use of local spatial information is crucial for obtaining good segmentation.

We propose to apply an advanced segmentation technique to snow µCT images: the energy-based segmentation (Boykov 2001). This method consists in finding the segmentation that minimizes a certain energy function. The definition of the energy makes the approach flexible and transparent by clearly expressing the segmentation criteria. The global optimization via graph cut makes the approach particularly robust and reproducible.

2. MATERIAL AND METHOD

2.1. Snow sampling and µCT measurements

Snow is a very fragile material. In particular, snow types involved in avalanche releases, such as depth hoar, are difficult to handle and require a specific sampling procedure (Flin et al. 2003). Once sampled in the field, the snow core is impregnated by liquid 1-chloronaphthalene («chl», melting point -15/-20°C) at temperature about -8°C. Then, the mixture ice/chl is allowed to freeze and stored in a refrigerator at −20°C. This sampling procedure strengthens the snow sample and blocks any possible microstructure evolutions due to metamorphism.

In this study, two types of snow with completely different grain shapes are considered (Figure 1). Sample 1 is a melt-freeze crust (MFcr according to the International Classification for Seasonal Snow on the Ground). Sample 2 is composed of depth hoar (DH) and faceted crystals (FC).

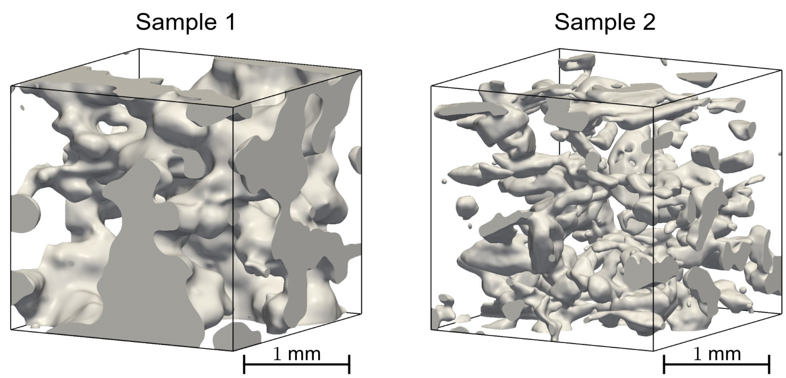

Figure 1: 3D representation of the snow microstructure of samples 1 and 2 (250^3 voxels).

The X-ray attenuation coefficient 3D images (about 1000^3 voxels) were acquired with a cone beam tomograph (RX Solutions, generator voltage of 100 kV, generator current 100 µA corresponding to a mean X-ray excitation energy of about 20 keV) using a specifically designed refrigerated cell (Flin et al. 2003).

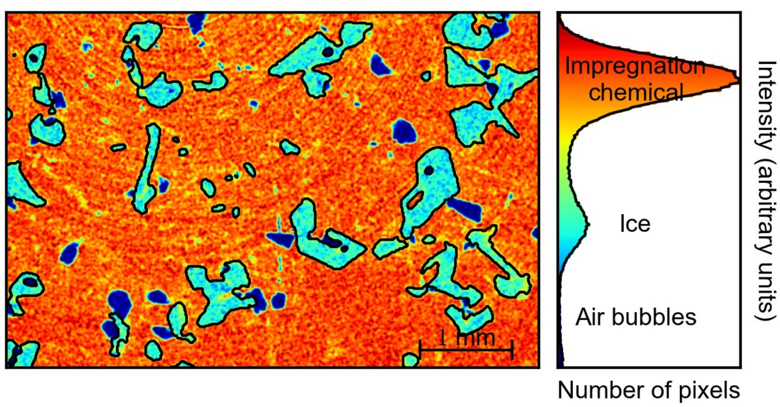

Figure 2: µCT output image (600*400 pixels) and its corresponding histogram. The scanned samples are composed of three materials: chl (red), ice (green/blue) and residual air bubbles (dark blue) due to an incomplete impregnation of the sample. The contour of ice resulting from the segmentation is plotted with a black line.

The µCT output images (Figure 2) are approximate representations of the X-ray attenuation coefficient and are affected by optical transfer function, scatter and noise. Thus, the grayscale image is noisy and the transition between different materials is fuzzy. In particular, contours of air bubbles in chl appear as ice envelops because of the partial volume effect. These artifacts yield to an important number of mixed voxels whose gray value does not determine whether they belong to the object or to the background. That is why the binary segmentation of µCT images is not straightforward.

2.2. Energy-based segmentation

The energy-based segmentation method consists in finding the optimal segmentation L according to an energy function E. This method is robust because the segmentation criteria are objectively defined in the energy function and the optimization process is global and automatic.

2.2.1. Energy function

The energy function of this study is composed of two terms: a data fidelity term and a regularization term.
The local gray value is the most obvious criterion in the segmentation process. For instance, a voxel whose intensity is very close to the intensity of air is inclined to be air, i.e., to belong to the background. This idea can be formalized with proximity functions P that penalize the segmentation of one voxel to ice or to the background. The proximity function ranges between 0 (furthest) to 1 (closest) and numerically quantifies the fidelity F(L) of the segmentation to the initial gray level of the voxel. The exact expression of the proximity functions might vary according to the grayscale image type. They are generally inferred from the analysis of the grayscale histogram out of which an intensity model is derived.
The surface area S(L) of the segmented object is, here, the spatial regularization term of the segmentation energy. A voxel with a mixed gray value will be segmented so that the interface ice/background area is minimized.
By assigning a relative weight r to the regularization term, the smoothness of the segmented snow can be controlled. The smoothness parameter r controls the minimum optical radius of protuberances of the segmented object. The size of the smallest structure details preserved by the segmentation is thus clearly defined.

2.2.2. Energy optimization

The established energy functional has to be minimized to find the optimal segmentation. For this purpose, the optimization of binary energies via graph-cut is well suited (Boykov et al. 2001). This method consists in transforming the binary energy optimization problem into the problem of finding an optimal cut in a graph, which is solvable in polynomial time. Unlike variational approaches, the optimization problem through graph-cut is directly defined on a discrete set of variables and the global optimality is guaranteed. A scalable graph-cut algorithm (Delong 2008) that enables the segmentation of massive grids was used in this work.

3. RESULTS

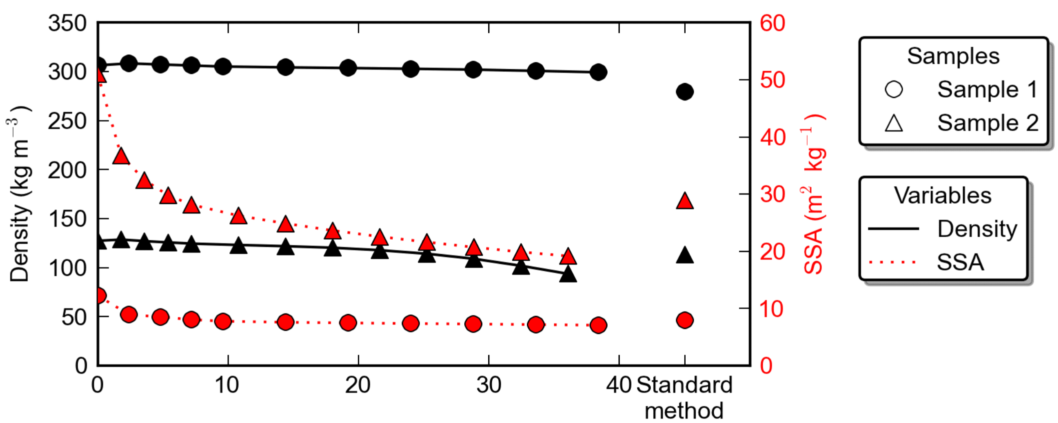

Figure 3: Density and specific surface area (SSA) as a function of the smoothness parameter r for two different snow samples.

Without an absolute reference, it is difficult to quantify the accuracy of the segmentation on µCT images. Therefore, the energy-based segmentation was first tested on a reference image degraded with artificial blur and µCT white noise. The Koch snowflake was chosen as a reference for its multiscale properties, allowing thus to check the method depending on the complexity of the physical object. On this synthetic image, the energy-based segmentation was found to be accurate above the size of the noise asperities.
The energy-based segmentation algorithm was then applied on the snow samples described previously for various values of the segmentation smoothness parameter. The results are consistent with standard segmentation methods (Figure 3) but, here, the segmentation parameters are more physically meaningful.

The segmentation parameter r affects structural variables as density and specific surface area (SSA) defined as the surface area per unit mass. The density of the segmented object does almost not vary with r (Figure 3). Density slightly decreases when r increases because the snow structure is generally convex and smoothing tends to erode convex zones. SSA is more sensitive to the segmentation parameter (Figure 3). Two regimes can be distinguished. For very low values of r (<5 µm for the considered images), the SSA decreases rapidly when r increases. This regime corresponds to the smoothing of the noise on the interface. For larger values of r, the SSA is constant or decreases slowly with r. For sample 1, composed of a melt-refrozen crust, there is no variation of the SSA with r because the interface is naturally already smooth. For sample 2, the SSA slightly decreases with r due to the sharpness of the considered sample. The real details of the snow structure contributing to the overall SSA are progressively smoothed down with an almost constant slope.
When the scale of noise is clearly separated from the detail scale as on sample 1, the segmentation parameter can be indifferently taken in the range [5, 40] µm. When these two scales are not clearly separated as on sample 2, the choice of r is more difficult. The best segmentation is obtained when most of the noise is smoothed, but the snow details are preserved. This segmentation may be obtained at the transition between the two described regimes, i.e. when the SSA starts to vary linearly with r.

4. CONCLUSION

The energy-based segmentation approach was successfully applied to microtomographic images of snow and leads to results that are in good agreement with those of standard segmentation methods. In addition, the presented method overcomes the limitations of threshold-based methods usually considered in snow research:

-The regularization term minimizing the ice/air interface is of particular interest for materials such as snow where sintering naturally tends to reduce the surface and grain boundary energy.

-The energy function is directly estimated on the segmented object, thus, the smoothness parameter defines the effective resolution of the binary image.

The influence of the smoothness parameter on density and SSA of segmented snow images has been investigated. This analysis emphasizes some important considerations to take into account in order to compute a reliable SSA value, especially for snow with structure details on the order of noise asperities.

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