

Feature Extraction on Digital Snow Microstructures

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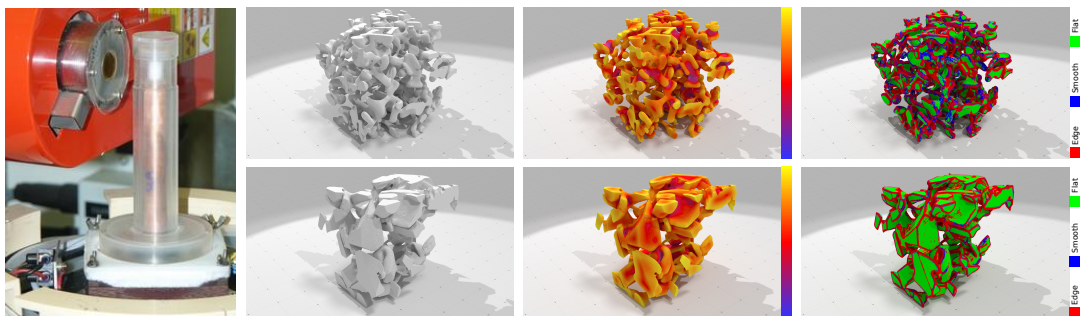


Figure 1: From left to right: Real snow sample and X-Ray microtomograph (courtesy of 3SR Lab and CEN/CNRM - GAME URA 1357/Météo-France - CNRS), digital snow microstructures, mean curvature estimation for fixed convolution ball R , feature extraction.

1 Introduction

During a snowfall, the snow crystals accumulate on the ground and gradually form a complex porous medium constituted of air, water vapour, ice and sometimes liquid water. This ground-lying snow transforms with time, depending on the physical parameters of the environment. The main purpose of the DIGITALSNOW project¹ is to provide efficient computational tools to study the metamorphism of real snow microstructures from 3D images acquired using X tomography techniques. We design 3D image-based numerical models than can simulate the shape evolution of the snow microstructure during its metamorphism. As a key measurement, (mean) curvature of snow microstructure boundary plays a crucial role in metamorphosis equations (mostly driven by mean curvature flow). In our previous work, we have proposed robust 2D curvature and 3D mean and principal curvatures estimators using *integral invariants*. In short, curvature quantities are estimated using a spherical convolution kernel with given radius R applied on point surfaces [Coeurjolly et al. 2014]. The specific aspect of these estimators is that they are defined on (isothetic) digital surfaces (boundary of shape in \mathbb{Z}^3). Tailored for this digital model, these estimators allow us to mathematically prove their multigrid convergence, *i.e.* for a class of mathematical shapes (*e.g.* C^3 -boundary and bounded positive curvature), the estimated quantity converges to the underlying Euclidean one when shapes are digitized on grids with gridstep tending to zero. In this work, we propose to use the radius R of our curvature estimators as a scale-space parameter to extract features on digital shapes. Many feature estimators exist in the literature, either on point clouds or meshes (“ridge-valley”, threshold on principal curvatures, spectral analysis from Laplacian matrix eigenvalues, ...). In the context of objects in \mathbb{Z}^3 and using our robust curvature estimator, we define a new feature extraction approach on which theoretical results can be proven in the *multigrid framework*.

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¹<http://liris.cnrs.fr/dsnow> (ANR-11-BS02-009)

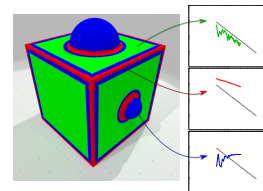
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2 Our Approach

The key point of the approach is to analyze the behavior of the curvature estimators when increasing the parameter R . In 2D, the curvature at a point x is estimated from the area $A_R(x)$ of the intersection between the spherical kernel and the object (for gridstep h): $\tilde{\kappa}_R(x) \stackrel{def}{=} \frac{1}{h} \left(\frac{3\pi}{2R} - \frac{3A_R(x)}{R^3} \right)$ [Coeurjolly et al. 2014]. We detail the estimator properties on three different cases: the flat case (zero curvature), the smooth case (constant curvature κ_0) and the edge case (singularity with angle α). For these three cases, we have:

$$\begin{aligned}
 & \text{Flat case: } A_R(x) = \frac{\pi R^2}{2} \Rightarrow \tilde{\kappa}_R(x) = 0 \\
 & \text{Smooth case: } A_R(x) = \frac{\pi R^2}{2} - \frac{\kappa_0 R^3}{3} \Rightarrow \tilde{\kappa}_R(x) = \kappa_0 \\
 & \text{Edge case: } A_R(x) = \frac{\alpha R^2}{2} \Rightarrow \tilde{\kappa}_R(x) = \frac{3}{2} \frac{1}{R} (\pi - \alpha)
 \end{aligned}$$

As a consequence, we design a multiscale approach to classify each digital surface element according to the behavior of $\tilde{\kappa}_R(x)$ when increasing R . For a flat object, $\tilde{\kappa}_R(x)$ should be zero (up to digitization artifacts that can be formalized, see dashed grey line in the image below); for a locally smooth patch, $\tilde{\kappa}_R(x)$ should lead to constant values. Finally, for singularities, $\tilde{\kappa}_R(x)$ should have a hyperbolic $O(R^{-1})$ behavior. The classification algorithm we propose is based on linear model fitting in logscale of $\tilde{\kappa}_R(x)$ values for a given range of radii. Finally, we use this classification for digital snow microstructure analysis



(*e.g.* to detect to crystallographic orientations or bonds between snow grains). A quantitative comparison with some state of the art methods is presented in supplementary materials. All materials presented here are available in the open-source library DGTal (<http://dgtal.org>).

References

COEURJOLLY, D., LACHAUD, J.-O., AND LEVALLOIS, J. 2014. Multigrid convergent principal curvature estimators in digital geometry. *Computer Vision and Image Understanding* 129, 27 – 41.