QUANTITATIVE COMPARISON OF SNOW PROFILES

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ABSTRACT: A snow profile, i.e. the variation of snow physical properties as a function of depth, captures the snow cover stratigraphy which is crucial for many applications such as the assessment of the avalanche danger. With the increasing use of distributed snowpack numerical models or electronic highly-resolved snow penetrometers, which generates a huge amount of data, there is a need for a robust and efficient method to compare and classify snow profiles. It has long been recognized that accounting for shifted layer position, i.e. layers at the same depth are not necessarily at the same position in the stratigraphic sequence, is crucial to obtain a meaningful metric. In this work, we present a new metric between snow profiles based on dynamic time warping that properly accounts for depth shifts in the stratigraphy. The new perspectives opened by this development are illustrated on three instances: the clustering of large spatially-distributed snowpack simulations, the correction of snowpack simulations with observed snow profiles and the quantification of the spatial variability of measured hardness profiles.

Keywords: snow stratigraphy; sequence alignment; matching; spatial variability

1. INTRODUCTION

The snowpack stratigraphy is generally described as the superposition of different slope-parallel layers (e.g. Fierz et al., 2009). It is often observed, however, that vertical snow profiles measured several meters from each other are different, making it difficult to identify one profile representative of the considered site. Such discrepancy between profiles is due to the snowpack spatial variability in terms of layer intensive property and layer depth. The variability of the layer depths causes stratigraphic mismatches: layers at the same depth are not necessarily at the same position in the stratigraphy. These stratigraphic mismatches make the comparison between profiles very difficult. Indeed, it is not really relevant to simply compare the measured property at the exact same depth in the different profiles (Lehning et al., 2001). For instance, Fig. 1 shows three different illustrative vertical profiles of a certain property. When computing the root mean square difference of these profiles depth-by-depth, it appears that profile 2 and 3 are the most similar, which is counter-intuitive. We would instead expect that profile 1 and profile 2 are the closest to each other because they share common stratigraphic sequences even if these sequences are shifted in depth.

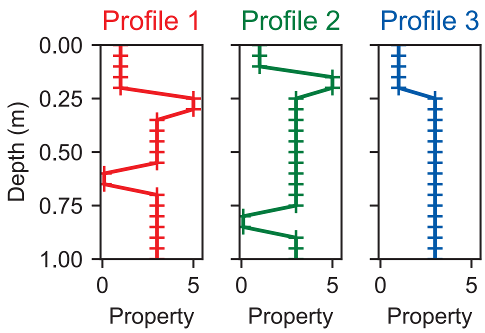

Figure 1: Qualitative comparison of three illustrative profiles. A depth-by-depth comparison of the profiles would identify Profile 2 and Profile 3 as the most similar. A layer-by-layer comparison of the profiles would identify Profile 1 and Profile 2 as the most similar.

The snow professional when comparing two manual snow profiles implicitly disentangles this interweaving of differences in property and depth positioning by identifying and comparing common stratigraphic sequences independently of their exact depth. Yet, with the increasing use of snowpack numerical models or electronic highly-resolved snow profilers (e.g. penetrometers) which generates a huge amount of data, this partitioning cannot be carried out manually and there is a need for an automatic method to compare snow profiles (Hagenmuller and Pilloix, 2016).

To this end, we adapted a method used for audio

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processing called dynamic time warping (Sakoe and Chiba, 1978; Schaller et al., 2016). This method enables to partition the difference between profiles into depth differences and differences of the considered intensive property. In this way, profiles that share the same crust or weak layer, but at different depths can be effectively recognized as similar and only differ by the position of the common feature.

The method is first presented and then used to solve three different problems: classification of simulated snow profiles, correction of simulated snow profiles with stratigraphy measurements and quantification of the snowpack variability.

2. METHOD

2.1. Layer mapping between two profiles

To quantitatively compare two profiles, it is necessary to perform a mapping between the layers of the two profiles. It means that it is necessary to explicitly identify and associate layers that are at the same position in the stratigraphic sequence. To this end, we followed the work of Hagenmuller and Pilloix (2016); Schaller et al. (2016). The main idea is to automatically adjust the layer thicknesses so that a certain distance D between the profiles is minimized. This distance D could be, for instance, the root mean square difference of hardness. In addition, the layer thickness extension or reduction is constrained in the range between -50% to +100% to avoid very large depth shifts. This constraint prevents from inversion in the layer order (bottom to top) and from very large layer dilation at the expense of the complete removal of some layers. To solve the optimization problem, i.e. finding the best thickness adjustments according to distance D, we use Dynamic Time Warping (Sakoe and Chiba, 1978). The minimal distance D obtained after layer mapping can be considered as a distance between the two profiles.

An example of a mapping between two illustrative profiles is shown in Fig. 2.

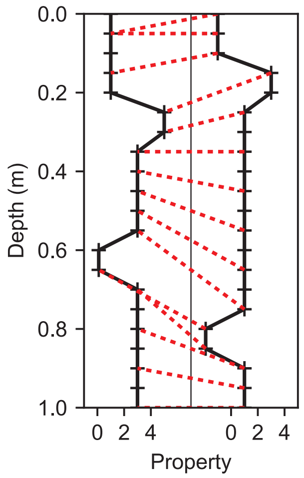

Figure 2: Mapping between two profiles. The profiles are shown in black. The mapping is represented by red dotted lines linking the profile points. For instance, the weak layer at a depth of 0.6 m in the first profile (left) is correctly associated to the weak layer at a depth of 0.8 m in the second profile (right).

2.2. Layer mapping between multiple profiles

To combine multiple (more than two) profiles together into one representative profile, the method described above does not apply directly. Indeed, no profile of the set can be arbitrarily considered as the reference profile and the other profile matched to this particular profile. Petitjean et al. (2011) proposed an heuristic approach to overcome this difficulty. Its main idea is to iteratively match the profiles to the mean of the matched profile, which thus evolves with the number of iterations. After a few iterations, the mean of the matched profiles converges into a profile that can be considered as representative of the profile set. This representative profile preserves sharp vertical property variations while a simple mean of the initial profiles would smooth this feature out.

3. RESULTS

3.1. Profile classification

The proposed method is here applied to classify profiles generated by large spatially distributed snow pack simulations.

Daily forecasts of the numerical weather prediction model (AROME) at 1.3-km grid spacing over the French Alps were used as atmospheric forcing to the snowpack model Crocus (Vionnet et al., 2016). This type of simulation generates a huge amount of data that cannot be reasonably analyzed manually. Indeed, it is very difficult to identify manually a common structure in this data. To reduce the amount of data, we propose to automatically group similar profiles together using the matching approach.

Firstly, the distance of each couple of profiles of the set is computed accounting for potential depth shifts. Then an agglomerative clustering technique is used to group profiles characterized by a small distance to each other. Lastly, the profiles belonging to the same cluster are matched together to derive a representative profile of each cluster. On the example of the Queyras massif shown in Fig. 4, the method identifies five consistent clusters. They correspond more or less to altitude bands with a pronounced East-West segmentation linked to the orientation of the principal meteorological fluxes (precipitation and wind).

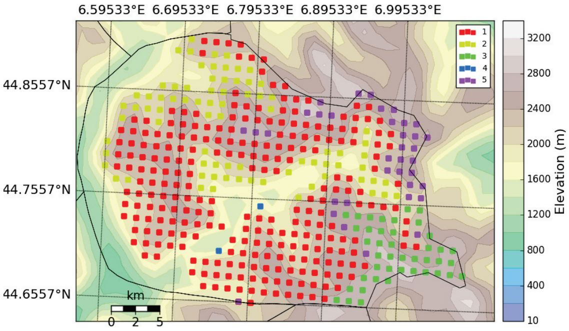

Figure 3: Classification of profiles simulated by the model chain AROME-Crocus on the Queyras massif, on March 2017. Each color represents a cluster. Only the spatial positions of the cluster are shown here but not the corresponding profiles.

3.2. Correction of snowpack simulations

The proposed method is here applied to correct snowpack simulations with measurements of snow stratigraphy.

On the one hand, manual stratigraphy measurements provide a direct screen-shot of the snowpack at the pit scale but they are time-consuming and only capture an instant of the snowpack evolution. On the other hand, numerical models provide estimates of the snowpack at a very high time resolution. Yet, these estimates can suffer from large deviations to the observed snowpacks because of errors in the meteorological forcing and limited accuracy in modelling complex but essential physical processes. It thus appears natural to combine these two sources of information to provide the best representation of the snowpack evolution.

The method proposed in this paper can associate each layer of the measured profile to the profile simulated at the measurement point. With this mapping, it becomes possible to re-initialize certain layer variables (e.g. layer thickness, grain size, density) of the simulation with direct measurements of the stratigraphy. Figure 4a shows the simulated snowpack at Col de Porte, France for winter season 2003-2004. The initial conditions of this simulation are the absence of snow in August 1, 2003. Large deviations from the observed snow depth are visible. Figure 4b shows the simulated snowpack corrected every week with snow stratigraphy measurements. As expected, the simulated snow depth is in good agreement with the measurements. More interestingly, the model with no correction simulates the presence of depth hoar at a height of 0.4 m in January 2003, while no observer has reported this presence. The corrected simulation effectively does not predict the presence of depth hoar. This difference may have important consequences to assess the avalanche risk.

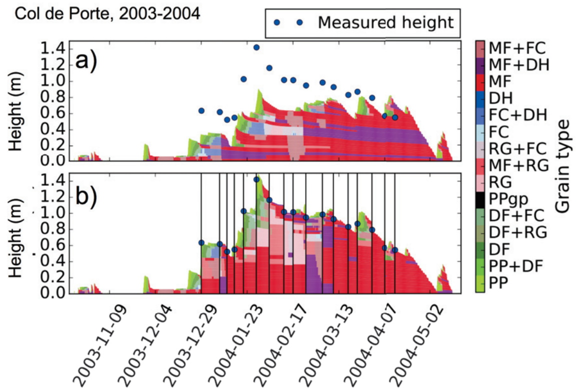

Figure 4: Correction of the snowpack simulation with measurements of the stratigraphy at Col de Porte, France, winter 2003-2004. (a) reference simulation without correction, (b) corrected simulation. Only the grain type profiles are shown here.

3.3. Quantification of the snowpack variability

The proposed method is here applied to evaluate the snowpack stratigraphy variability.

Snow stratigraphy was captured using a digital snow micro penetrometer (SMP) in a spruce beetle infested forest in the Uinta Mountains, Utah, USA, over the course of winter 2015 - 2016. Repeated measurements on fixed 20 m transects were conducted every 0.5 m in four different study plots: meadow area, harvested forest, gray forest attacked by spruce beetle and green healthy forest. On the raw hardness data, it is impossible to disentangle the interweaving of vertical and spatial (horizontal) variabilities. Indeed, the spatial variation of hardness at a given depth is both affected by the spatial variability of the snowpack hardness but also the spatial variability of the layer depth and the vertical variability of hardness. For instance, Fig. 5a shows an example of the hardness profiles measured under the harvested forest. It is easy to follow the different layers manually but impossible to quantify the spatial variability. To this end, the proposed method is very efficient and enables to match all measured profiles so that they are aligned (Fig. 5b). The spatial variability can then be simply computed as the mean standard deviation along the transect. By repeating this procedure on all the data, we were able to compute an indicator of the snowpack spatial variability as a function of the canopy closure (Fig. 5c). We observed that the spatial variability is mainly controlled by canopy closure with no specific visi-

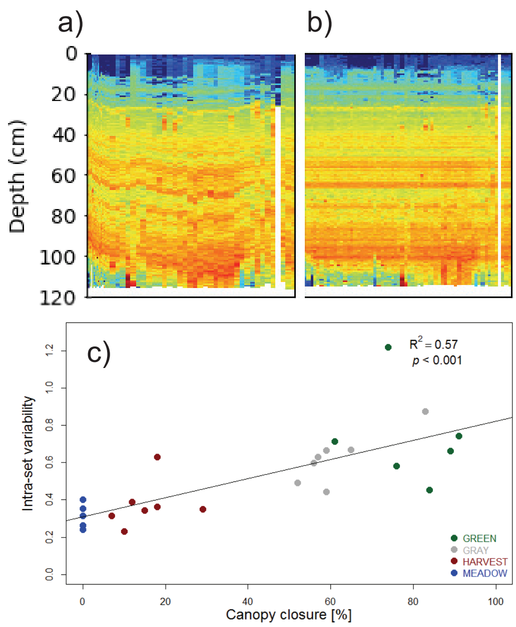

Figure 5: Analysis of snowpack spatial variability under different types of forest. (a) hardness profile transect measured under harvested forest. A blue color means low hardness, a red color means high hardness. (b) same profiles but aligned. (c) Intra-set variability, an indicator of spatial variability as a function of canopy closure.

4. CONCLUSION

The spatial variability of layer depth makes any quantitative comparison between profiles difficult. The proposed method successfully enables to vertically align snow profiles so that continuous layers are at the same depth. It is based on a robust algorithm, Dynamic Time Warping, initially used for audio signal processing. Despite its simplicity, the method has many practical applications as the ones illustrated in this paper.

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