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Refining the processing of paired time series data to improve velocity estimation in snow flows

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ABSTRACT

For effective avalanche risk mitigation, numerical models with a correct description of snow rheology are needed. Conventionally, velocity in snow flow experiments is inferred by cross-correlating the voltage signals of paired sensors. The intention of this paper is to reconsider this problem to enhance processing of these data, leading to more effective estimates of fluctuating velocity quantities. The algorithm consists of a wavelet decomposition, a denoising step and a weighting method for the reconstituted signal. The resulting velocity time series are both consistent and informative, providing confidence that one can analyse not only the mean velocity profiles, but also the velocity distribution. Our approach is illustrated using a typical chute experiment undertaken at Col du Lac Blanc in the French Alps. Not only has the mean velocity profile a more complex shape than the bilinear one postulated from the results of the standard cross-correlation processing, but the probability distribution functions of the velocity at different heights is much more continuous and dispersed, revealing interesting new patterns of greater dynamical relevance.

1. Introduction

Snow avalanches constitute a significant natural hazard in mountain environments, e.g. Fayes and Lakhdar (2000). In addition to socio-economic considerations, effective risk analysis requires knowledge of both the frequency of occurrence of events (Eckert et al., 2008, 2013) and information on the dynamics (Keylock and Barbolini, 2001) to evaluate vulnerability accurately (Keylock et al., 1999; Fuchs et al., 2005; Eckert et al., 2012; Favier et al., 2014). Specifically, evaluating runout distances and impact pressures as function of return period (Ancey et al., 2004; Eckert et al., 2008, 2007) requires effective numerical models of avalanche dynamics. These have progressed from sliding block formulations (Voellmy, 1955; Perla et al., 1980; Dent and Lang, 1983; Salm et al., 1990; Gauer et al., 2009) to continuum formulations of the conservation of mass and momentum for an "avalanche fluid", with drag typically defined in terms of a Coulomb basal resistance, a velocity-dependent resistance (Barbolini et al., 2000; Gray et al., 2003), with additional terms also included for extensive and compressive effects (Bartelt et al., 1999), or basal erosion (Naaim et al., 2003; Christen et al., 2010).

Yet, there is still significant uncertainty in our knowledge of the dynamics of these flows and, thus, the relevant flow physics. Insights into the salient dynamics may be gained from analysing radar data for the full flow field (Ancey and Meunier, 2004; Issler et al., 2005; Gauer et al., 2008; Rammer et al., 2007; Sovilla et al., 2008; Kohler et al., 2016), particularly with the development of higher resolution radar systems (Vriend et al., 2013; Ash et al., 2014). However, more carefully controlled, fundamental studies that aim to elucidate the properties of flowing snow are still essential to facilitate the development of appropriate constitutive laws (Dent et al., 1998; Kern et al., 2004; Schaefer et al., 2010).

The particular experiments that underpin this work differ from earlier studies in that an attempt was made to establish a steady-state flow in the chute to assist in constraining the rheology of flowing snow (Bouchet et al., 2003; Rognon et al., 2008). From this work, three flow regimes were identified as a function of slope: a decelerated flow below about 33 °, an accelerated flow above about 41 ° and a steady and uniform flow regime between these two limits. Increasing the slope angle over a set of experiments gave an abrupt transition from zero velocity below ~33 ° to a constant value of ~3 m s^{-1}. This constant then increased steadily to ~4 m s^{-1} at ~41 °. Beyond this limit, the flow was accelerating. This behaviour may be contrasted with that of a yield stress fluid where there is a continual increase in mean velocity with slope angle beyond the yield stress threshold. Within the steady

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flow regime, the vertical mean velocity profile was fitted by a bilinear function. Hence, in terms of the rheological behaviour, the dense flow of dry snow appeared to be composed of two layers: a strongly sheared basal layer made up of individual snow grains and a less sheared upper layer made up of larger aggregates (Rognon et al., 2008).

To extract velocity information from experiments such as these, significant processing of the raw voltage signals is necessary. The standard approach has been to cross-correlate the signals from neighboring sensors a known distance apart (Dent et al., 1998; Bouchet et al., 2003) to derive a mean velocity at a point and, therefore, a mean velocity profile. However, it is difficult using this approach to obtain information on the velocity fluctuations, which are critical for estimating flow properties such as granular temperature and, therefore, for understanding the rheology of flowing snow.

To obtain such information from existing datasets, a new approach to data processing is required. In this paper, we reinvestigate the rheological behaviour of the dense flow of dry snow following the application of our signal processing methodology. We first outline the properties of the data considered, before processing them with the standard Maximum Cross-Correlation (MCC) method. The new algorithm, a wavelet-based denoising method, is then presented and its efficacy compared to the MCC approach. On a typical Col du Lac Blanc chute experiment, we are able to show that our approach produces velocity signals that retain much greater information content with respect to the fluctuations.

2. Data

Experiments were performed at the Col du Lac Blanc pass near the Alpe d'Huez ski resort in the French Alps, located at an altitude of 2830 m. This high altitude gives access to large amounts of natural snow between January and April, and data were obtained during the 2004–2006 winters. The set-up and instrumental devices were previously described in Bouchet et al. (2003, 2004) and Bouchet (2003) and the flow geometry and feeding system of the experimental procedure were described in Rognon et al. (2008) and Rognon (2006). In brief, one hundred experiments were undertaken with various slopes (the inclination of the channel), flow depths and temperatures. Seventy-five of them generated a sufficiently steady flow during which all sensors were operational, making them amenable to analysis. Each experiment was allocated an arbitrary two letter code that is also adopted in this study to enable comparisons to be made between studies using these data. In this paper we focus on the experiment denoted "BU" as an illustrative example. It was performed with a flow depth of $H \sim 9.5$ cm, the air temperature was $T_{air} = -10\,^{\circ}$C and the slope was $\theta = 37^{\circ}$, corresponding to a steady and uniform regime. Hence, it is at an intermediate slope angle with respect to the bounds on a steady flow (33°–41°), with a depth towards the upper end of the range observed for steady flows of 4–12 cm (Rognon et al., 2008).

2.1. Velocity sensors and voltage signals

A description of the various sensors is provided to contextualise the signal processing undertaken herein. The data acquisition system consists of three different type of sensors: three depth sensors, H1, H2, H3, and 13 pairs of velocity sensors, as well as a normal stress sensor and a basal stress sensor (Schaefer, 2015). The latter were not used in the analysis for this study explicitly, although both the depth sensors and stress sensors were used to determine if a steady state flow had developed (Rognon et al., 2008, chap. 3).

The height and stress sensors were located on the chute centre-line and the velocity sensors in a vertical column within the working section (where the steady-state profile was obtained), and on the outside of the chute, with data acquired at a frequency of 10 kHz. A velocity sensor is made from an upstream and a downstream pair of photodiodes and phototransistors separated by a distance, $d = 7.20$ mm (Fig. 2). The sensors operate by emitting infrared light from a photodiode. A part of the emitted infrared beam spreads in the snow and another part is reflected back to the phototransistor, which acts as a receiver (Dent et al., 1998; Bouchet et al., 2003). Consequently, the raw data are voltage signals generated by the reflection of infrared light, and the nature of the resulting signals is related to the properties of material reflection as well as the material morphology. Snow particles passing near the sensor cause a significant departure from the 5 V baseline voltage. For each sensor location (height), an upstream voltage signal, X_t, and a downstream, Y_t, are used to estimate the flow velocity over a period of about 8 s (Section 3). This estimation is based on the time lag that gives the greatest similarity between X_t and Y_t and the separation distance between upstream and downstream sensors.

The times series of flow depths were used to determine the duration of the experiment (shown below in Fig. 3), as well as the number of useful velocity sensors (those that remained below the mean flow depth for the duration of the experiment).

3. Maximum Cross-Correlation (MCC) approach to velocity estimation and optimal window size determination

A steady and uniform regime was established so that rheological inferences could be made. A steady flow is one where the depth-integrated velocity does not exhibit a trend through time — it is not accelerating or decelerating. A uniform flow is one where the mean velocity profile remains constant in shape rather than evolving in time, meaning that properties such as mean shear rate can be inferred from the velocity profile in a meaningful fashion. For experiments with a steady and uniform flow, there is an initial increase in flow depth as the front moves through the working section, a region with constant mean behaviour and then a waning flow. This structure to the dynamics was used as a constraint to identify the start and end of the data series analysed (Fig. 3). For experiment BU, over the various heights, the duration of the steady flow period was between 7.37 s and 14.68 s, with the minimum used to ensure a constant analysis duration for all heights.

The inclination of the channel and the location of the instrumentation were such that the flow direction was from right to left. Consequently, a constraint on the analysis is that the peak in the cross-correlation of the upstream signal, $X(t)$, and downstream signal, $Y(t)$, must have a lag that respects this directionality. The maximum cross correlation (MCC) method has been adopted previously for studying the velocity characteristics of flowing snow (Dent et al., 1998; Rognon et al., 2008) and gives the time lag, Δt_{ξ}, for which X_t most resembles (in a linear sense) the series $Y_{t+\Delta t_{\xi}}$:

$$\Delta t_{\xi} = \arg\{\max_{1 \le i \le n_{win}} (\mathrm{Corr}(X_t, Y_{t+i}))\} \qquad \xi \in \left[\!\left[1; \left\lfloor \frac{n}{n_{win}} \right\rfloor \right]\!\right]. \tag{1}$$

Therefore, we can estimate $\left\lfloor \frac{n}{n_{win}} \right\rfloor$ velocity measurement points provided the length of both voltage series is n. A crucial issue with this technique is that the MCC depends on the window size for correlation, n_{win}. This parameter cannot be chosen arbitrarily as its influence is particularly notable when attempting to recover the dynamics of the velocity series.

3.1. New window size for correlation

In previous work, e.g. Rognon et al. (2008), the velocity fluctuations were disregarded and $n_{win} = 1000$ (i.e. 0.1 s) was used for correlation. Such a long period for the window over-smoothes the dynamics and while it is eminently suitable for evaluating the mean velocity, it proves to be unsuitable for estimating fluctuating velocities. Given that n_{win} over-smoothes the data, much smaller window sizes should be considered in order to study the influence of the window on the velocity estimation, and to determine the optimal window size. Fig. 4 shows the MCC method applied to one pair of voltage signals using different