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Snowpack stability information derived from the SnowMicroPen signal

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Abstract

Snowpack measurements and stability tests are, next to recent avalanche activity and weather history, currently the basis for snowpack stability assessment in most avalanche warning operations. The SnowMicroPen (SMP), a high-resolution penetrometer for snow, measures penetration resistance force or snow hardness. In order to be useful for an avalanche warning service, stability information needs to be provided and must be derivable from the SMP signal. SMP profiles (25 on slopes, 14 on flat sites) were taken together with manual snow profiles and stability tests, such as Rutschblock and compression tests. The data are from three winter seasons of the years 2001–2002 to 2003–2004 in the Swiss Alps. According to their stability test score and failure interface properties the manual profiles were classified as stable or unstable. Based on the manual observations the failure interfaces were identified in the SMP profiles and possible indicators of instability were derived from the SMP signals at these interfaces. The distinct indicators of instability were the failure layer micro-structural length and hardness, the difference in structural length across the failure interface and the failure layer macro-elastic modulus. The cross-validated accuracy of classification into stable or unstable failure interfaces gained from SMP parameters was comparable to the classification accuracy from manual profile parameters (about 65%). It remains to be tested if stability information can be derived from a SMP measurement without knowing the location of the failure interface found by a stability test. If this can be done successfully and reliably, avalanche warning operations could definitely benefit from the instrument.

Keywords: Snowpack stability; Avalanche forecasting; Snow profile; Mechanical properties; Snow hardness

1. Introduction

Manual snow profiles combined with snowpack stability tests are currently the most reliable snowpack records considered for stability evaluation in avalanche forecasting (McClung and Schaerer, 1993). Schweizer and Jamieson (2003) provided a stability classification method based on the Rutschblock score, failure layer hardness, failure layer grain size, the difference in grain size and hardness across the failure interface. With their classification model, it was estimated that at least 65% of the manual profiles could be classified correctly when compared to adjacent avalanche activity or stability test scores (Schweizer and Jamieson, 2003). These results show the significance of the mechanical and structural properties of the failure interface in respect to snowpack stability.

The SnowMicroPen is a high-resolution snow penetrometer (Schneebeli and Johnson, 1998). It quickly measures the penetration resistance of snow at high resolution. Johnson and Schneebeli (1999) derived structural and mechanical parameters from the SMP

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Table 1
Data set used: number of failure interfaces

Profile type	Stable	Unstable
Flat field	12	4
Slope	23	10

signal based on a micro-structural model. Based on statistical approaches to larger data sets, Schneebeli et al. (1999) and Pielmeier and Schneebeli (2003) have derived stratigraphical, mechanical and structural information from the SMP signal.

Since the winter of 2002–2003, the Swiss avalanche forecasting service has been testing the operational applicability of the SMP. Forecaster's snow profiles and stability tests were complemented by SMP measurements. The goals were to provide SMP training, technical improvement of the SMP, and data collection. The aim of this study is to explore whether and how the SMP profile is related to snowpack stability. Since snowpack stability is related to failure interface properties and the SMP signal includes structural and mechanical information at high resolution, it was expected that stability could also be predicted from the SMP profile.

To test this hypothesis, we analyzed the combined snow profiles. We classified the manual profiles as stable or unstable according to the method introduced by McCammon and Schweizer (2002) and quantified by Schweizer and Jamieson (2003) and Schweizer et al. (2007). The stability test failure interfaces were identified in the corresponding SMP profiles and subdivided into a failure layer, a transitional layer and an adjacent layer. The mechanical and structural properties of the failure interfaces were determined from the SMP profiles. Statistical analysis was used to determine the significant SMP parameters indicating stability and to calculate their combined predictive power in terms of failure interface stability. The results were compared to those of the manual profile classification (Schweizer and Jamieson, 2003; Schweizer et al., in press).

2. Data

The original data set from the winter seasons of 2002–2003 and 2003–2004 consisted of 47 profiles. However, in 14 cases significant SMP signal drift made the profile unusable for the analysis. The erroneous signal drift was attributed to melt water or condensation water affecting the SMP force sensor during the measurement. Improved sealing of SMP tip shaft and cables as well as new ventilation holes in the shaft and careful drying were applied to counteract the drift problem and to reduce the number of defective records. The remaining 33 snow profiles with 39 failure interfaces were complemented by 6 combined snow and SMP profiles with 10 failure interfaces originally collected to study spatial variability during the winter seasons of 2001–2002 and 2002–2003 (Kronholm, 2004).

Finally, the data set consisted of 39 snow profiles with 49 failure interfaces (Table 1). Most of the profile locations were chosen for the operational assessment of regional avalanche danger. The profiles consisted of a manual profile, a stability test and a SMP measurement. The SMP measurement was taken slope perpendicular, adjacent to the manual profile.

3. Methods

3.1. Manual snow profiles

The manual profiles were taken according to the guidelines of the International Classification for Seasonal Snow on the Ground (Colbeck et al., 1990). The Rutschblock test (Föhn, 1987) was performed on slopes. At flat profile locations, the compression test was used and its test score was converted to a Rutschblock score according to Jamieson (1999). Based on the stability test, the failure layer (FL_{man}) and the adjacent layer (AL_{man}) across the failure interface were defined. For each FL_{man} and AL_{man} the hand hardness, grain size, grain shape and the depth of the failure plane were used for the analysis. Also, the absolute grain size difference and hardness difference across the failure interface were used. The threshold sum approach as proposed by McCammon and Schweizer (2002) was used for stability classification. If five or more criteria of the list in Table 2 were fulfilled at the failure interface (i.e., threshold sum ≥ 5), the manual profile was classified 'unstable' (Schweizer et al., 2007). Otherwise, it was classified 'stable'.

Table 2
Critical ranges of Rutschblock score, mechanical and textural parameters of a potentially unstable failure interface (Schweizer et al., in press)

Parameter	Critical range
Rutschblock score	<4
Grain size difference	≥ 0.75 mm
Grain size	≥ 1.25 mm
Hardness difference	≥ 2 hardness indices
Hardness	≤ 1–2
Grain shape	Facets, depth hoar or surface hoar
Layer depth	≤ 1 m

3.2. SnowMicroPen profiles

A similar procedure was performed on the SMP profiles to calculate the layer properties at the failure interfaces. We used a layer definition procedure similar to Birkeland et al. (2004) and Kronholm et al. (2004). By superimposing the manual profile and the stability test result on the SMP profile the failure interfaces as well as the upper and lower boundaries of layers were defined by visual inspection of each SMP profile. Since the SMP profile is not a discrete but a continuous record of the snow properties, the failure interface was defined not in two layers, as was done in the manual profiles, but in three layers: a failure layer (FL_{smp}), a transitional layer (TL_{smp}) and an adjacent layer (AL_{smp}). An example of the SMP layer definition is shown in Fig. 1. Birkeland et al. (2004) showed that small inconsistencies in the visual layer definition procedure (up to ±5% of the total layer thickness) can be neglected. The following mechanical and structural properties of the defined SMP layers were calculated: FL_{smp} thickness, FL_{smp} mean hardness, absolute and relative hardness difference between FL_{smp} and AL_{smp}, FL_{smp} texture index (Schneebeli et al., 1999), absolute and relative texture index difference between FL_{smp} and AL_{smp}. The relative differences were calculated by taking the ratio of the AL_{smp} parameter and the FL_{smp} parameter. The force discontinuities in the transitional layer were fitted with a linear model as well as with a 'robust' least absolute deviation method, the latter model being less sensitive to outlying data (Ebdon, 1985). The modeled force gradients of the transitional layers were also analyzed.

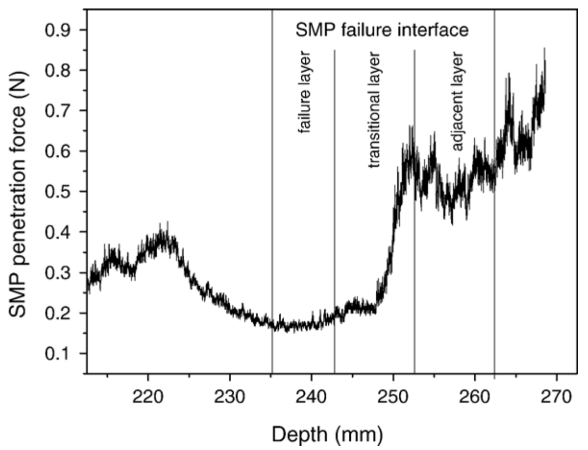

Fig. 1. Section of an SMP profile containing a failure interface. The stability test caused a failure at a depth of 240 mm (distance below snow surface). The vertical lines delineate the three manually defined SMP layers at the failure interface: failure layer (FL_{smp}), transitional layer (TL_{smp}) and adjacent layer (AL_{smp}).

Table 3
Stable–unstable comparison of SMP variables

SMP parameter	*n* stable	*n* unstable	*p*-value
FL thickness	34	14	0.674
FL mean hardness	34	14	**0.028**
Absolute difference hardness	31	14	0.091
Relative difference hardness	31	14	0.659
FL texture index	35	12	0.770
Absolute difference texture	19	10	0.963
Relative difference texture index	19	10	0.608
Slope of linear fit at TL	31	14	0.194
Slope of robust linear fit at TL	31	14	0.270
FL structural length	32	13	**0.008**
Absolute difference structural length	32	13	**0.040**
Relative difference structural length	32	13	0.140
FL structural size	32	13	0.168
Absolute difference structural size	32	13	0.341
Relative difference structural size	32	13	0.239
FL macro-elastic modulus	31	13	**0.034**
FL macro-compressive strength	31	13	0.055

The sample size and the level of significance of the univariate analysis (*U*-test) are given. The significant variables ($p<0.05$) are bold.

Further structural and mechanical SMP parameters studied were based on the micro-structural model developed by Johnson and Schneebeli (1999) and applied by Kronholm (2004). The micro-structural parameters we analyzed are FL_{smp} mean structural dimension or length (LN) and calculated grain dimension (LS), absolute and relative difference in LN and LS between FL_{smp} and AL_{smp}. LN is the micro-structural element length that can be related to the number of element failures and the area of the measuring tip during a certain distance of SMP penetration. LS is the micro-structural element size derived from LN and the calculated density. A correlation to observed grain size of manual profiles was not found (Kronholm, 2004) which was attributed possibly to the effect of grain shape. The mechanical parameters we analyzed were FL_{smp} macro-elastic modulus and macro-compressive strength. Both parameters are related to the SMP force at the rupture of micro-structural elements during penetration. Kronholm (2004) compared the calculated SMP macro-compressive strength and elastic modulus to published values of compressive strength and Young's modulus. For the SMP macro-compressive strength a fair agreement was found, whereas for the macro-elastic modulus the calculated values were about two orders of magnitude lower than the literature data (Kronholm, 2004).

To compare the SMP data from the stable and unstable profiles we used the non-parametric Mann–Whitney U-test (Spiegel and Stephens, 1999). A level of significance $p=0.05$ was chosen to decide whether the observed differences were statistically significant. A non-parametric test was chosen because it is independent of population distribution and associated parameters. For multivariate analysis the classification tree method (Breiman et al., 1998) was used to find the best classifier. The data were split into consecutive subsets. Optimal splits were based on a least square loss function with a minimum proportion reduction in error at any split and a minimum split index value of 0.02 at any node of the classification tree. From the results of the classification tree, we further calculated the predictive power of the significant SMP parameters.

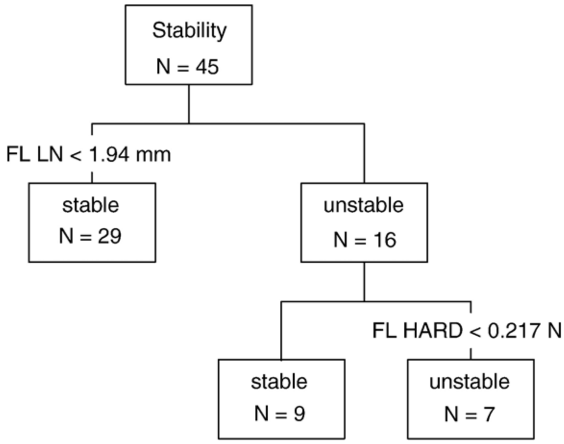

Fig. 3. Classification tree for the non-cross-validated stable/unstable data set ($n=45$). The overall classification accuracy was 75%. The data set contained FL_{smp} structural length and FL_{smp} mean hardness as independent variables.

4. Results

4.1. Univariate analysis of SMP profiles

The results of the statistical analysis of all SMP parameters for the stable and unstable profiles are shown in Table 3. Based on the univariate analysis (U-test), the FL_{smp} structural length ($p=0.008$) was the most significant SMP parameter to classify between stable and unstable failure interfaces. The failure layers in unstable profiles had larger structural lengths than in stable profiles. This agrees well with practical experience and the fact that bonds are weak if grain size differences are large (Colbeck, 1991). Further, the FL_{smp} mean hardness ($p=0.028$) was significant. Unstable profiles showed smaller failure layer hardness than stable ones. Also, the FL_{smp} elastic modulus ($p=0.034$) was significant, with smaller elastic modulus for unstable profiles than for stable ones. Finally, the absolute difference in structural length between AL_{smp} and FL_{smp} ($p=0.040$) was found to be a significant variable. A larger difference in structural length was observed in unstable profiles than in stable ones. The distributions of the significant variables are shown in Fig. 2. The FL compressive strength ($p=0.055$) and the absolute difference in hardness between FL_{smp} and AL_{smp} ($p=0.091$) were the variables with low, but not significant p-values.

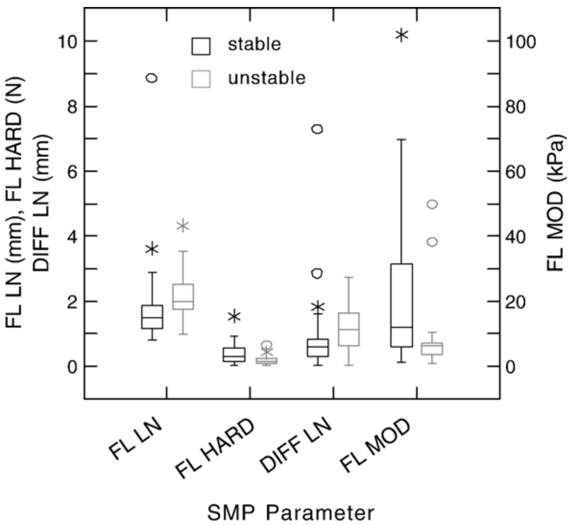

Fig. 2. Contrasting stable (left) and unstable (right) failure interfaces for the variables FL_{smp} structural length (FL LN), FL_{smp} mean hardness (FL HARD), difference in structural length (DIFF LN) and FL_{smp} elastic modulus (FL MOD). The boxes represent the interquartile range from the first to the third quartiles with a horizontal line showing the median. The whiskers show the range of data that fall within 1.5 times the interquartile range above and below the interquartile range. Asterisks show outlying data, and circles far outlying data.

Table 4
The classification scores of the learning sample ($n=45$)

Predicted	Observed		
	Stable	Unstable	Total
Stable	25	4	29
Unstable	7	9	16
Total	32	13	45

The classification accuracy was 75%.

Table 5
The classification scores of the cross-validated half samples (n=23/n=22)

Predicted	Observed		
	Stable	Unstable	Total
Stable	11/11	2/3	13/14
Unstable	6/4	4/4	10/8
Total	17/15	6/7	23/22

The overall classification accuracy was 65% and 68%.

4.2. Multivariate analysis of SMP profiles

For the prediction of our categorical dependent variable (stable/unstable) we used a classification tree. We selected the four independent variables that were statistically significant in the univariate analysis (Table 3). Because of the strong correlation of FL_{smp} mean hardness to FL_{smp} macro-elastic modulus and of FL_{smp} structural length to difference in structural length across the failure interface, only FL_{smp} mean hardness and structural length were relevant in the multivariate analysis. The tree hierarchy and the splitting values are shown in Fig. 3. From this analysis, SMP failure interfaces were predicted to be unstable if FL_{smp} structural length $\geq$1.94 mm and FL_{smp} mean hardness <0.217 N.

The learning sample (n=45) used to calculate the tree had an overall classification accuracy of 75%. The false-stable prediction rate was 9% (4/45) and the false-alarm rate was 15% (7/45), shown in Table 4. If stable conditions were always assumed, the false-stable prediction rate would be 29% (13/45). Since an additional sample for verification was not available, we split the learning sample for this purpose in half and used one half as learning and the other as verification sample, and vice versa. A reduction of about 10% in classification accuracy is usually expected from this procedure. When the complete data set was randomly split in half, the mean classification accuracy was reduced to 67%, shown in Table 5. Hence, the cross-validated classification accuracy gained from SMP parameters lies close to the one estimated for manual profile parameters (65%). To have a more balanced data set, the stable data set was randomly split in half and the unstable data set was taken completely. The mean classification accuracy was again 76%. This suggests that the fact that our data set is unbalanced did not affect classification accuracy.

5. Discussion

The study suggests that the following SMP parameters are indicators of snow instability: FL_{smp} structural length, FL_{smp} mean hardness, difference in structural length across the failure interface and FL_{smp} macro-elastic modulus. These parameters are related to the indicators from manual profiles and to dry snow slab avalanches. The ranking of the significant SMP parameters was similar to the ranking of the significant manual profile parameters. Measures of FL structural dimension are in both cases most significant indicators of instability followed by measures of FL hardness. The classification tree calculated with manual profile parameters (Schweizer and Jamieson, 2003) resulted in different splitting parameters. There, the classification tree split on the first level with the difference in grain size across the failure interface. On the second level, it split once with the FL_{man} mean hardness and once with the difference in hardness across the failure interface. Not all manual parameters were replicated by the SMP profile, which is in part due to the different nature of the measurement.

Considering the spatial variability of the snowpack, Kronholm (2004) showed that comparing the one-dimensional SMP profiles with the two-dimensional stability tests is valid. Improvements are needed in the identification of the failure interface in SMP profiles. Further knowledge of the failure process at the failure interface and its relation to the SMP signal is also needed. We are aware that the data basis for the statistical analysis is still small.

6. Conclusions

With a small combined data set of manual and SMP snow profiles, we found characteristics of failure interfaces calculated from the SMP signal that indicate instability. The classification tree method showed that failure layer structural dimension and hardness were not only indicators of instability in manual profiles but also in SMP profiles. The classification tree can be used as preliminary model to classify failure interfaces in regard to stability with parameters calculated from a SMP profile. The accuracy of classification into stable or unstable profiles based on SMP parameters was comparable to the one achieved with manual profile parameters. Improvements should be made in the SMP failure interface identification and by expanding the data set primarily with unstable profiles.

A next step will be to test how well stability can be predicted from an unclassified SMP profile, i.e., without a priori determining the failure interface with the help of the manual observation. If a reliable failure interface detection and stability prediction from SMP profiles is possible, avalanche warning operations could benefit from the instrument since snowpack data collection would be simplified and expedited. SMP signal drift made about one third of the original data set unusable for the analysis. Improvements in signal drift detection and signal drift reduction will also be necessary to make the SMP an operational field instrument for avalanche warning purposes.

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References

Birkeland, K., Kronholm, K., Schneebeli, M., Pielmeier, C., 2004. Changes in shear strength and micropenetration hardness of a buried surface-hoar layer. Ann. Glaciol. 38, 223–228.

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., 1998. Classification and Regression Trees. CRC Press, Boca Raton, U.S.A. 368 pp.

Colbeck, S.C., 1991. The layered character of snow covers. Rev. Geophys. 29 (1), 81–96.

Colbeck, S.C., Akitaya, E., Armstrong, R., Gubler, H., Lafeuille, J., Lied, K., McClung, D., Morris, E., 1990. The international classification of seasonal snow on the ground. International Commission on Snow and Ice (ICSI), International Association of Scientific Hydrology, Wallingford, Oxon, U.K. . 23 pp.

Ebdon, D., 1985. Statistics in Geography. Basil Blackwell, Oxford. 232 pp.

Föhn, P.M.B., 1987. The Ruthschblock as a practical tool for slope stability evaluation. In: Salm, B., Gubler, H. (Eds.), Symposium as Davos 1986 - Avalanche Formation, Movement and Effects, IAHS Publ., 162. International Association of Hydrological Sciences, Wallingford, Oxfordshire, U.K., pp. 223–228.

Jamieson, B., 1999. The compression test—after 25 years. Avalanche Review 18 (1), 10–12.

Johnson, J.B., Schneebeli, M., 1999. Characterizing the micro structural and micro mechanical properties of snow. Cold Reg. Sci. Technol. 30 (1–3), 91–100.

Kronholm, K., 2004. Spatial variability of snow mechanical properties with regard to avalanche formation. Ph.D. thesis, University of Zürich, Zürich, Switzerland, 158 pp.

Kronholm, K., Schneebeli, M., Schweizer, J., 2004. Spatial variability of micro-penetration resistance in snow layers on a small slope. Ann. Glaciol. 38, 202–208.

McCammon, I., Schweizer, J., 2002. A field method for identifying structural weaknesses in the snowpack. In: J.R. Stevens (Editor), Proceedings ISSW 2002. International Snow Science Workshop, Penticton BC, Canada, 29 September–4 October 2002. International Snow Science Workshop Canada Inc., BC Ministry of Transportation, Snow Avalanche Programs, Victoria BC, Canada, pp. 477–481.

McClung, D.M., Schaerer, P., 1993. The Avalanche Handbook. The Mountaineers, Seattle, WA, U.S.A. 271 pp.

Pielmeier, C., Schneebeli, M., 2003. Stratigraphy and changes in hardness of snow measured by hand, ramsonde and snow micro penetrometer: a comparison with planar sections. Cold Reg. Sci. Technol. 37 (3), 393–405.

Schneebeli, M., Johnson, J.B., 1998. A constant-speed penetrometer for high-resolution snow stratigraphy. Ann. Glaciol. 18, 193–198.

Schneebeli, M., Pielmeier, C., Johnson, J.B., 1999. Measuring snow microstructure and hardness using a high resolution penetrometer. Cold Reg. Sci. Technol. 30 (1–3), 101–114.

Schweizer, J., Jamieson, J.B., 2003. Snowpack properties for snow profile analysis. Cold Reg. Sci. Technol. 37 (3), 233–241.

Schweizer, J., Jamieson, J.B., Fierz, C., 2007. A threshold sum approach to stability evaluation of manual snow profiles. Cold Reg. Sci. Technol. 47 (1–2), 54–63.

Spiegel, M.R., Stephens, L.J., 1999. Schaum's outline of theory and problems of statistics. Schaum's Outline Series. McGraw-Hill, New York, U.S.A. 538 pp.