SNOW-PACK STRUCTURE: STABILITY ANALYZED BY PATTERN-RECOGNITION TECHNIQUES

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ABSTRACT. Internal snow-cover structure depicted by conventional snow profiles is commonly held to be important for avalanche forecasting but it is largely omitted from numerical forecasting schemes owing to quantification difficulties. A subjective test given to practising forecasters illustrated the complex roles of measured profile parameters in describing instability. A clustering technique of pattern recognition, after introducing a snow-profile training set, has demonstrated an objective ability to sort correctly 86% of the layer boundaries associated with slab-avalanche bed surfaces or lubricating layers. Further improvement in stability recognition comes from a newly devised shear test driven by a wedge which quickly locates failure planes within the snow cover. The cluster analysis is then able to sort with similar accuracy between stable and unstable (avalanching) failure planes so located.

RÉSUMÉ. *Structure du manteau neigeux: analyse de la stabilité par des techniques de reconnaissance de formes.* La structure interne du manteau neigeux caractérisée par des profils conventionnels de battage est généralement considérée comme un élément important pour la prévision des avalanches mais est fréquemment omise dans les schémas de prévision numériques en raison de la difficulté de les quantifier. Un test subjectif, auquel on a soumis des prévisionistes praticiens, illustre le rôle complexe des paramètres mesurés d'un profil dans la description de l'instabilité. Une technique automatique de reconnaissances de formes, après introduction d'un ensemble de profils de neige d'entraînement, a prouvé une possibilité objective de reconnaître correctement 86% des limites des couches servant de plan de glissement d'avalanches de plaques ou de niveau de lubrification. De nouvelles améliorations dans la reconnaissance de la stabilité sont apportées par un dispositif de mesure du cisaillement récemment mis au point, constitué par un coin qui repère rapidement les plans de rupture à l'intérieur du manteau neigeux. L'analyse automatique est alors capable de reconnaître, avec une précision analogue, les plans de rupture stables ou instables (avalancheux) ainsi localisés.

ZUSAMMENFASSUNG. *Struktur der Schneedecke: Stabilitätsanalyse mit Verfahren der Mustererkennung.* Die innere Struktur der Schneedecke, ermittelt aus konventionellen Schneeprofilen, wird gewöhnlich als wesentlich für die Lawinenvorhersage angesehen, bleibt aber infolge von Schwierigkeiten in der Quantifizierung bei numerischen Vorhersageverfahren weitgehend unberücksichtigt. Ein subjektiver Test mit Vorhersagepraktiken erwies die komplexe Rolle von gemessenen Profilparametern bei der Beschreibung der Instabilität. Eine Cluster-Technik der Mustererkennung eröffnete nach Einführung eines Trainingssatzes von Schneeprofilen einen objektiven Weg zur mit 86% richtigen Aussonderung jener Schichtgrenzen, die mit der Auflagefläche von Schneebrettern oder mit Schmierschichten verknüpft sind. Eine weitere Verbesserung in der Stabilitätsanalyse ist von einem neu entwickelten Schertest zu erwarten, der einen Keil zur schnellen Lokalisierung von Ebenen grosser Nachgiebigkeit in der Schneedecke benutzt. Die Clusteranalyse ist dann in der Lage, mit ähnlicher Genauigkeit zwischen stabilen und instabilen (Lawinen verursachenden) Nachgiebigkeitsebenen zu unterscheiden, die so gefunden wurden.

NUMERICAL models for avalanche forecasting are currently being developed and used throughout the world (Judson and Erickson, 1973; Bois and others, [1975]; Salway, unpublished). Nearly all of these models are statistically based on a wide collection of meteorological data. These models allow a fairly good prediction of direct-action avalanches but, because snow-pack information is minimal, they are less effective for delayed action or climax events. Since snow-pack structure is an integral part in assessing slope stability, its inclusion would enhance the efficiency of avalanche forecasting. This present study develops a quantified stability analysis through an objective evaluation of snow-pack structure.

Interpretation of snow-pit data hitherto has depended on the *ad hoc* development of collection and transmission procedures. This is reflected in the subjective nature of many of the measurement parameters and their obscure relations to the mechanics of snow-slab failures. Our analysis addresses these problems in three parts. The first part seeks to understand how practising forecasters recognize unstable features in a snow-pit profile. The second part uses a multivariate statistical method in the form of pattern recognition to discriminate stable and unstable measurement parameters within snow layers. The third part introduces an objective measurement describing stability.

PART I. RECOGNIZING STABILITY BY SUBJECTIVE INSPECTION

The first step to recognizing patterns in snow-pack structure was a subjective test given to 58 practising forecasters. Thirty fracture-line profiles were gathered from several areas in the United States, Canada, and Switzerland, the actual bed surfaces for the observed slabs were masked and the participants

were asked where they believed a sliding surface could exist within each snow-pack. The tests were scored by calculating the mean error; that is, the distance of the chosen surface away from the actual bed surface. The scores were correlated to the number of years of experience of each forecaster and where that experience was obtained.

Although small sample sizes prohibit statistical inferences, some preliminary generalizations of the results (Fig. 1) suggest slight variations among profiles from different regions. For instance, the Wasatch Mountains profiles showed lower mean errors than profiles from other areas. This may reflect either the field investigator's bias or the actual climatological character of the snow-pack. People evaluating profiles from their home region gained no score advantage, but more experienced forecasters has slightly lower error scores in every region. Experience with profile graphs and field forecasting may be separate skills, not readily discernible from this type of test.
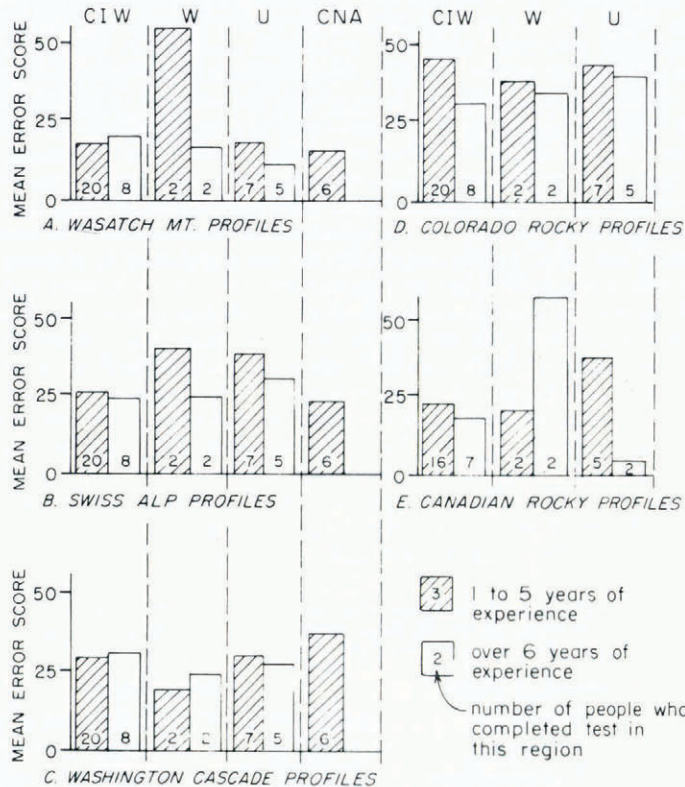

Fig. 1. *Fracture-line profile-test results. A, B, C, D, and E contain profiles from the Wasatch Mountains in Utah, Swiss Alps, Washington Cascades, Canadian Rockies, and the Colorado Rockies, respectively. The dashed lines separate people with experience in Colorado, Idaho, and Wyoming (CIW), Washington (W), Utah (U), and California, New Mexico, and Arizona (CNA).*

Each profile was evaluated by comparing the actual bed surface to the sliding surface chosen by the majority of forecasters, whether the most popularly chosen surface was above, below or coincided with the actual bed surface. The profile patterns which were consistently identified incorrectly had subtle instabilities at the bed surface, whereas correctly chosen surfaces had more familiar, obvious discontinuities. When asked which parameters were important for recognizing planes of failure, the forecasters tended to isolate those parameters which displayed the most distinct discontinuity. For instance, ram resistance may have held the most information in one profile, while stratigraphy in another profile gave more clues to instability. A forecaster soon learns to recognize obvious discontinuities, like crusts as bed surfaces and depth hoar as lubricating layers, as indicators of avalanche potential. Subtle snow features

characterizing instability take more experience to recognize. For example, some snow-packs had enough load stress from the upper layers to break through a crust to a lower bed surface between layers of coarse-grained old snow, and beginning temperature-gradient metamorphism often proved more unstable than fully developed depth hoar.

This test illustrated the complex role of each parameter in describing instability. Even though the major features of these parameters are readily recognized, it is not always these major features which describe unstable properties within a snow-pack. A more objective look at the features and properties of snow-pit information is required.

PART II. RECOGNIZING STABILITY BY CLUSTER ANALYSIS

A multivariate analysis of snow-cover profiles provided a basis for clustering techniques in a pattern-recognition computer program (Duewar and others, unpublished) derived from standard statistical methods (Fukunaga, 1972). After a suitable training set of snow profiles was introduced, data points clustered into characteristic patterns which were recognized as stable or unstable. Our training set consisted of 14 measurement parameters (Table I) from stable snow profiles and unstable fracture-line profiles. Since the number of measurements is large and the number of available profiles is small, several selection and combination processes were performed on these parameters to find the best method of reducing the size of the data matrix. Five dimensions were retained, representing linear combinations of the measurement parameters and a weighted selection of those parameters and features containing the largest variance of information. These five dimensions were plotted and the program then isolated and categorized the resulting cluster patterns. The categories were then correlated to known classifications of layer stability within each snow profile and a criterion was established for defining stability by how well the clusters of points represented actual characteristics of the training-set data. Measurement parameters from the bed surfaces and lubricating layers of fracture-line profiles were designated unstable. Stable parameters came from two other adjacent layers within those same fracture-line profiles which were not involved in avalanching. Each data unit comprised parameters from layers both above and below a real or possible failure plane. The measurements for each layer were density, ram resistance, temperature, hand-test hardness, crystal type, layer thickness, and tangential stress. Since the hand-test hardness and crystal type are not in numerical form, they were quantified by a system which maximized the necessary information and minimized any extraneous information inherent in the scaling process.

Once these measurements were quantified, uniformly scaled, and reduced to form a five-dimensional data matrix, they were displayed on two-dimensional scatter diagrams. Figure 2 is an example of a plot where the numbers 1 and 2 refer to unstable and stable profiles, respectively. Here the axes are linear

TABLE I. SNOW-PROFILE MEASUREMENT PARAMETERS AND THEIR COMBINATIONS USED IN THE CLUSTER ANALYSIS. THE TOP LAYER (T) AND THE BOTTOM LAYER (B) ARE THOSE LAYERS ADJACENT TO A REAL OR POTENTIAL BED SURFACE AND LIE DIRECTLY ABOVE AND BELOW IT, RESPECTIVELY

Original measurement parameters		Retained features	
		Linear combinations*	Orthogonal selection
1. Top layer	T-thickness		
2. Top layer	T-density	1. B-density	1. T-crystal type
3. Top layer	T-ram resistance	T-shear stress,	2. B-crystal type
4. Top layer	T-temperature	T-density,	3. B-ram resistance
5. Top layer	T-hand test	B-temperature, ...	4. T-ram resistance
6. Top layer	T-crystal type	2. B-ram resistance,	5. B-hand test
7. Top layer	T-shear stress	T-ram resistance,	
8. Bottom layer	B-thickness	T-crystal type,	
9. Bottom layer	B-density	T-hand test, ...	
10. Bottom layer	B-ram resistance	3. B-crystal type,	
11. Bottom layer	B-temperature	B-hand test,	
12. Bottom layer	B-hand test	T-hand tests, ...	
13. Bottom layer	B-crystal type	4. B-thickness,	
14. Bottom layer	B-shear stress	T-thickness, ...	
		5. B-thickness,	
		T-temperature,	
		B-temperature,	
		T-hand test, ...	

* Only those parameters which retain more than 50% of the total feature variance are shown.

combinations of parameters. The abscissa is a feature dominated by density, stress, and temperature. The ordinate represents a combination of ram resistance, crystal type and hand-test hardness. This two-dimensional view of a five-dimensional space displays a recognizable clustering of unstable profiles. When all five dimensions are combined and a least-squares multi-layer regression is performed, 86% of the stable and unstable categories can be properly discriminated. This means that, if we were to introduce a profile of unknown stability, we can be 86% assured that it will be categorized correctly.

When stable and unstable layers were separated into actual and potential lubricating layers and bed surfaces, it was found that 83% of the unstable lubricating layers could be so classified, whereas only 72% of the unstable bed surfaces could be properly classified. Recognizing possible bed surfaces, like crust layers, may be necessary to describing instability but it is not sufficient. Results from the fracture-line profile test in Part I corroborate this observation.
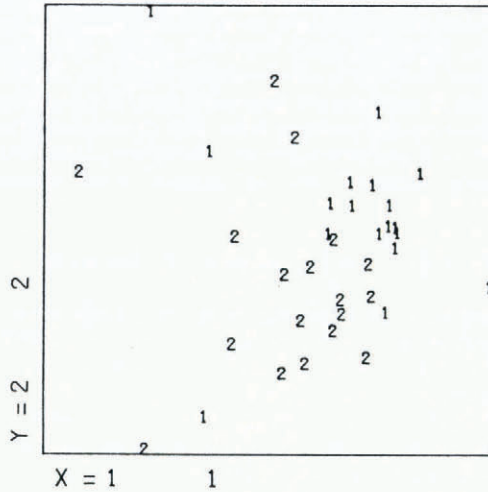

Fig. 2. *First data feature (B-density, T-shear stress, T-density, B-temperature, . . .) of all the measurement parameters versus the second data feature (B-ram resistance, T-ram resistance, T-crystal type, T-hand test, . . .). Unstable snow layers (1) and stable snow layers (2) are shown.*
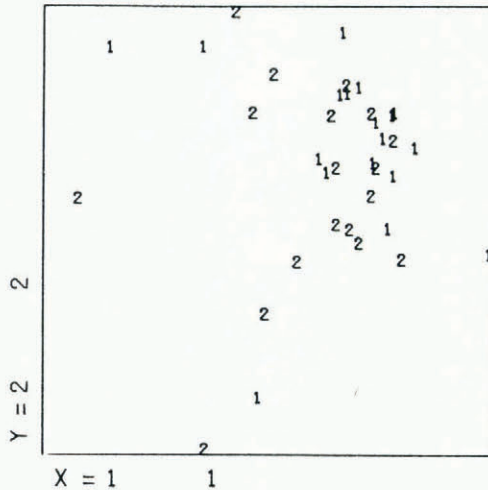

Fig. 3. *First data feature (B-shear stress, T-shear stress, B-density, T-density, . . .) of the measurement parameters, excluding crystal type, and the hand test versus the second data feature (B-ram resistance, T-ram resistance, . . .). Unstable snow layers (1) and stable snow layers (2) are shown.*

An assortment of routines was tested for feature reduction, plotting, and category discrimination with varying degrees of success. One evident trait throughout each routine was the consistent selection of hand-test hardness and crystal type as important to classification. Figure 3 is a two-dimensional plot similar to Figure 2 except crystal types and hand-test hardnesses have been omitted. The points within each category are more highly scattered and discrimination efficiency between stable and unstable layers has been reduced to 75%. Although these are the two most subjective measurements, they describe characteristics of a snow layer which cannot be ignored when defining stability. A better quantitative definition of these parameters would improve stability evaluation.

PART III. RECOGNIZING STABILITY BY FAILURE PLANES

Identifying potential sliding surfaces from inspection of snow-pit stratigraphy is often an empirical judgement based on subjective measurements like crystal type and hand-test hardness. Because these potential sliding surfaces and lubricating layers are essential to slab-avalanche formation, a more direct system of finding them has been developed which improves on the "shovel test" commonly used in the field. This follows the principle of working in a low-entropy data space outlined by LaChapelle (1980).

A simple wedge was designed to impart a shear stress to snow layers. This wedge was placed at the back of a vertical column of snow cut out on three sides (Fig. 4) and forced vertically downward with a hammer on a guide rod, similar to a ram penetrometer. As failure planes developed and blocks of snow slid off the column, their "wedge number", W_n, an estimate of the layer-parallel component of the applied force, was recorded.

$$W_n = \left(\frac{nfH}{p} + m\right) \sin \beta \cos(\theta - \beta) + h\rho g \sin \theta$$

where n = the number of blows with the hammer, f = the fall height of the hammer, H = the weight of the hammer, p = the penetration depth of the wedge, m = the weight of the wedge plus the hammer, θ = the slope angle, β = the wedge angle, h = the slab thickness, ρ = the mean density of overlying slab layers, and g = the acceleration of gravity.

A prototype of this instrument was tested in the Cascade Mountains during the winter of 1978–79. Failure planes were readily located and relative values of W_n were obtained. This test set of data was derived from snow-packs known to be stable either after the use of explosives or from settlement. The
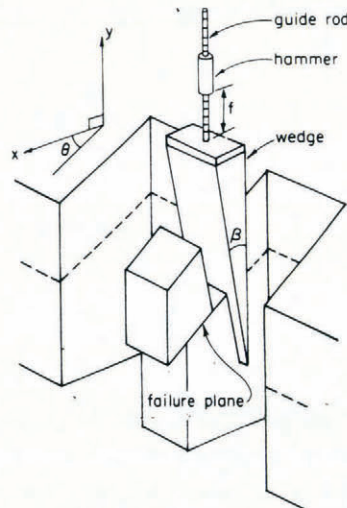

Fig. 4. A snow wedge vertically driven into the backside of a snow column to find failure planes within a snow-pack. The slope angle is θ and the wedge angle is β.

layers within each profile which had the lowest wedge number, those most likely to become the failure plane of a slab avalanche, were introduced in the pattern-recognition program described in Part II. 89% of these stable profiles were properly discriminated from the previously available unstable fracture-line profiles. Therefore the location of shear planes within a snow-pack does not by itself imply instability, for the shear strength at failure also must be measured. Preliminary wedge numbers from a limited set of actual avalanched snow surfaces were significantly different from known stable surfaces.

The fact that a multivariate analysis could distinguish stable from unstable shear planes implies that the necessary information to describe stability quantitatively is available in the snow-pit measurements. Since a wedge can locate failure planes and their relative contributions to avalanching can be estimated by the clustering of their measurement parameters, it may no longer be necessary to gather complete measurements throughout the depth of a snow-pack. Rather, a quick identification and stability classification of failure planes may provide useful structural criteria for inclusion in numerical avalanche forecasting schemes.

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