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Integrating Neural Networks and Rule Based Systems to build an Avalanche Forecasting System

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Abstract
A new approach to the problem of avalanche forecasting is presented. A hybrid expert system called ALUDES[1] was developed to assess the avalanche danger for a given region. Using snow, weather and snow cover data as input parameters the system evaluates the degree of danger for a given region. It integrates extended symbolic computing from traditional Artificial Intelligence and connectionist methods using Kohonen Networks. By generating (symbolic) fuzzy-rules with the *fuge*[2]-method from subsymbolic data through exploring the structure of a Kohonen Network it becomes possible to explain the behaviour of a Kohonen Net.

Keywords
Snow avalanche forecasting, neural networks, fuzzy-rule extraction, hybrid expert systems

1. Introduction

Snow avalanches represent a typical and frequent hazard in mountainous regions. Hence avalanche forecasting and protection by avalanche barricades is essential for the development of mountain regions and tourism.
In Switzerland the Swiss Federal Institute for Snow and Avalanche Research (SFISAR) is in charge of the public avalanche warning for the whole area of the Swiss Alps [1]. Any tools providing assistance for this difficult task are welcome. Present diagnosis tools are mainly based on statistical treatment of daily assessed snow and weather data. To improve and to homogenize the decision process of avalanche forecasting, a new system is developed with the following objectives:

- assessment of the degree of avalanche danger on the basis of daily snow and weather data
- ability to use incomplete or inconsistent data
- ability to explain the result (degree of danger)
- better overall performance than existing systems
- better performance in critical situations

During another avalanche forecasting project ([2]) a large database of weather, snow and avalanche data has been built up at the SFISAR. The database consists of about 1200 days (eight winters) for the Parsenn area (Davos/Grison). Each day includes 14 parameters describing the weather and state of the snowcover and the degree of the avalanche danger (seven degrees form 1 to 7) for this day. This degree of danger for each day was verified by experts at the SFISAR and is used as class variable. This large database suggests the use of a connectionist system. Those are able to *generalize*, to work with *incomplete* or *inconsistent* data. Nevertheless they lack transparency. They are black-box systems like present approaches, where the rules leading to an avalanche danger assessment cannot be explained to a user. This problem can be solved by combining connectionist models and knowledge based systems. By integrating the two approaches it is possible to eliminate the weakness of each single method by exploiting the strength of the other [3,4].
The type of neural network used is the Kohonen Network (KN, [5]). A KN is built up through an input-layer consisting of nodes each of which holds the value of a parameter and a 2-dimensional network of nodes called *feature-map*. The two layers are fully connected. A trained KN realizes a topology-preserving projection of a n-dimensional input space to the 2-dimensional feature-map (hyperplane). The *weights* of the connections of a node of the feature-map to the nodes of the input-layer represent the projected parameter-values of the days projected to this area of the feature-map. Using this structure of a KN and the new *fuge*-method presented below it is possible to generate *fuzzy-rules* that are able to explain the behavior of a KN.
The method presented below may be used to generate an explanation system to a KN or as an example-based knowledge acquisition tool.

1. ALUDES is the spanish word for "avalanche".
2. *fuge* is the abbreviation for *fuzzy-generator*.

2. *fuge* - a new method to extract fuzzy-rules out of a Kohonen Net

The *fuge*-method is based on a trained KN. The method uses the results of an exploration of the structure of a KN [6] described below. The *fuge*-method consists of the extraction of *membership-functions* out of a KN and an algorithm to generate fuzzy-rules using only the *relevant* components. *Membership-functions* allow to formulate conditions in fuzzy-rules in natural-language terms and to measure the degree of which the condition is true. In fuzzy logic the '*whether*' of traditional logic represented by the values *1* or *0 (true* or *false)* is replaced by '*how much*' represented by values in the range [0,1].

An overview over the procedure of fuzzy-rule extraction is showed in Fig. 1. First, the feature-map of a trained KN is divided into different non-overlapping regions, corresponding to clusters in the dataspace of the training samples or given classifications of the samples. If no classifications are given the feature-map can be structured using the *U-Matrix* method [5]. With this method it is possible to visualize clusters in a n-dimensional samplespace on the 2-dimensional feature-map of a KN using the mean distance of the weight vector of each node of the feature-map to the weight vectors of its four direct neighbours. This allows to divide the map into different regions corresponding to different clusters in the samplespace. This regions or clusters can be interpreted as (sub-)classes. If, on the other hand, a classification is given for each sample, a supervised version of the self-organizing learning procedure of a KN may be used. Including

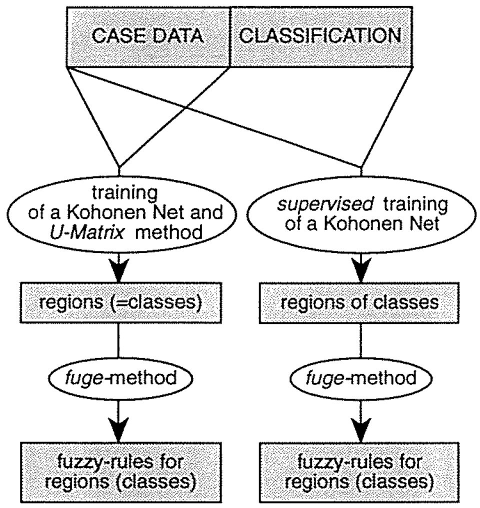

Fig. 1 Extraction of fuzzy-rules if no classification is given (left) or classification is given (right).

the classification as an input parameter the feature-map of a KN can be divided into different regions using the value of the learned weight connected to the input node representing the classification. So the regions found correspond to the classes.

If the feature-map of a KN could be divided into different regions using one of the two methods described before, the *fuge*-method explained in the next section is used to extract membership-functions and to generate fuzzy-rules for each region (class).

2.1 Extraction of membership-functions

Using the partition of the feature-map of a KN into different regions (classes) it is possible to extract *membership-functions* using the weights of the KN in a way similar to the U-Matrix method. The membership-functions for all parameters are extracted for each region (class). For a given region r and parameter p, the mean distance $d_k^{r,p}$ of the weight w_k^p corresponding to the parameter p is calculated between each node k of the region and its direct neighbour-nodes. So for

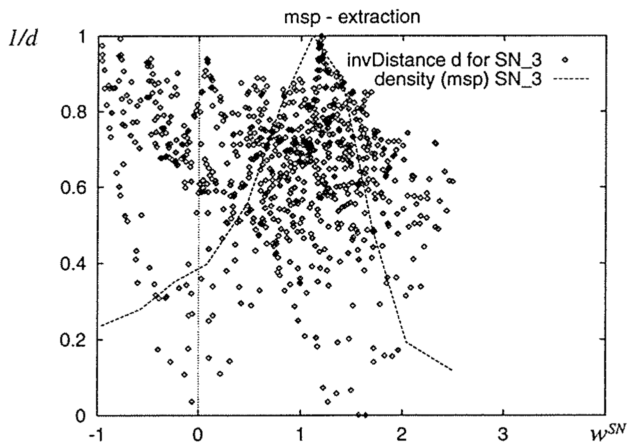

Fig. 2 Example of a plot of points $(w^{SN}, 1/d)$ and corresponding density-function (see text for explanation).

each region r and parameter p a plot can be generated using the points $(w_k^p, 1/d_k^{r,p})$ for each node k of the region. An example of a plot for a parameter (called *SN*) of a specific class (degree of danger 3) is shown in Fig. 2. A possible approximation of the membership-function is the density-function of the w-values of the points (see also Fig. 2). The maximal value of the membership-function and $1/d$ are normalized to 1.

This procedure is based on the fact, that the distribution of the nodes on the feature-map of a KN corresponds to the distribution of the points in the dataspace because of the *topology-preserving* projection of the dataspace onto the feature-map. This global aspect used in the U-Matrix method is in the method described above reduced to the local aspect of a single parameter (only *one* component of the weight vector is used to calculate the mean distance).

If the density-function of the w-value is used to approximate the membership-function the distance d is redundant information that only shows the correspondence between the density of the w-values and the calculated distances d.

2.2 Production of fuzzy-rules

For each region (class) a fuzzy-rule could be written now by using conditions of *all* parameters in the premis of the rule. Such a rule would be hard to read. So, the idea is to generate rules using only *relevant* parameters in their premis. To improve the readability of the rules further, the premis of each main-rule for a class is divided into two parts. The first part formulates conditions using parameters that differentiate well to *all* other classes. The second part refers to sub-rules that differentiate well to specific other classes. The main-rules and sub-rules have the following form:

main-rule:

IF *fuzzy-condition_A_para1* AND
fuzzy-condition_A_para2 AND
...
diagnosis is more class A than B AND
diagnosis is more class A than C AND
...
THEN *diagnosis is class A*

sub-rule:

IF *fuzzy-condition_AB_para1* OR
fuzzy-condition_AB_para2 OR
...
THEN *diagnosis is more class A than B*

The condition *fuzzy-condition_A_para1* has to be interpreted for example as "*IF parameter1 IS low*", where "*low*" is the linguistic approximation of the membership-function extracted for *parameter 1* of the class *A*. The membership-functions (i.e. for the *fuzzy-condition_AB_para1*) of the sub-rule conditions can easily be calculated using the basic membership-functions (i.e. *fuzzy-condition_A_para1* and *fuzzy-condition_B_para1*). The algorithm to select the relevant parameters for a rule and to formulate the sub-rules is based on the examination of the overlap of the membership-functions for all parameters between all pairs of classes. This method selects the most relevant parameters and generates fuzzy-rules that are easy to read.
Which AND/OR-operator to use for the propagation of the membership-values of the fuzzy-rules depends on the classification problem and has to be determined by tests.

3. ALUDES - a hybrid expert system for avalanche forecasting

The architecture of the *hybrid expert system for avalanche forecasting* is shown in Fig. 3. It includes a **Kohonen Net** and a **rule base** (RB) consisting of *structure rules* (fuzzy-rules, generated out of the KN with the *fuge*-method). Other rules, called *direct rules* (generated with standard machine learning algorithms, like ID3) and *other rules* (generated by

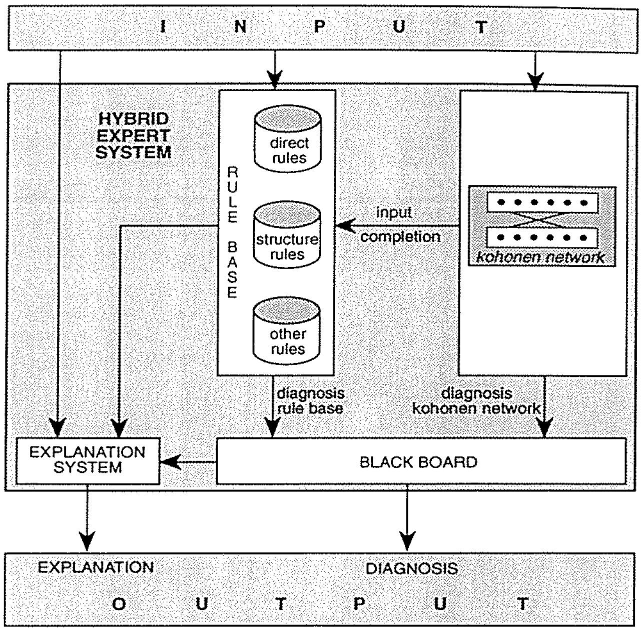

Fig. 3 Architecture of the hybrid expert system ALUDES.

experts through other knowledge acquisition methods) could be added to the RB. Both the rule base and the KN perform a diagnosis that is combined in a **blackboard** (BB) to a final diagnosis. The results of this two components KN and RB showed, that the RB performs better for the avalanche danger classes 4, 5 an 6, while the KN performs better in the classes 1, 2 and 3 (degree of danger 7 never occurred in the dataset). So the strategy of the BB is to propagate the diagnosis of the RB if the classification of the RB is 4, 5 or 6 and to propagate the diagnosis of the KN in all other cases.
The KN works also with incomplete data. Using only the known parameters a diagnosis can be given and default values for the missing parameters can be determined. So the RB is able to calculate a diagnosis with the parameter set completed by the KN.
By including a rule base, consisting of 26 *structure rules*, the lack of explanation capability of the KN can be resolved in cases where the diagnosis of the KN and the RB correspond.

4. Results

To develop and test the system the data of eight winters (1210 days) was used. First results show, that about 69% of the system-diagnosis are correct (see *test set*, Tab. 1). A test set consisted of one winter (151 days), while the learn set was composed of the remaining seven winters each time. Each learn set then was learned with about 84% correctness. To improve the generalization capability of the KN for future winters *all* available eight winters where learned with 80% correctness (see *learn set*, Tab. 1). So it should be possible to improve the result of 69% in future winters.

The diagnosis of the fuzzy-rules can be compared to the

sets (# cases)	% correct	% to low	% to high
learn set (1210)	80	10	10
test set (mean of 3 sets of 151 days)	69	17	14

TABLE 1. Performance of the KN.

expected diagnosis (verification of degree of danger) and the diagnosis given by the KN (see Tab. 2). The first comparison corresponds to the correctness of the fuzzy-rules, while the latter indicates the explanation capability of fuzzy-rules relating to the KN. The reason why the explanation capability is not clearly better than the correctness of the diagnosis can not be given at this time. Further examples have to be explored to see whether the reasons of this result are based on the *fuge*-method or on type of the problem treated.

diagnosis of fuzzy-rules compared to ...	% correct	% to low	% to high
... verification	58	16	26
... KN diagnosis	61	13	26

TABLE 2. Performance of the fuzzy-rules.

The fuzzy-rules generated by the *fuge*-method use, according to the experts of the SFISAR, the most relevant parameters for the different classes of the avalanche danger. Nevertheless the rules formulate only *general* conformities with natural laws and allow no deeper insights into the physical dependences of the avalanche forecasting problem. Nevertheless the generalization capabilities of the fuzzy-rules can be observed for higher classes of the avalanche danger (4, 5 and 6). This classes are represented in the dataset of totaly 1210 days only through 50 days. Using only the relevant parameters the fuzzy-rules perform better than the KN for this days.

Compared to other forecasting systems ALUDES shows about the same performance as the best statistical based systems used so far. An advantage of the system that includes a Kohonen Net is the robustness and ability to work with incomplete data. Further, an explanation in natural language terms for a diagnosis can be given in about 60% of the cases using fuzzy-rules.

5. Conclusions

The new approach showed to be a powerful method to the problem of avalanche forecasting. ALUDES is a reliable support system for the decision process which directly evaluates the degree of avalanche danger for a given region.

Using the *fuge*-method, it is possible to extract (symbolic) knowledge in form of fuzzy-rules out of a connectionist system that uses sub-symbolic knowledge. The generated fuzzy-rules are able to explain the behavior of the KN used in ALUDES in 61% of the cases. So the lack of transparency of neural networks can partially be overcome.
Comparing the diagnosis of a KN and the diagnosis of fuzzy-rules generated out of this KN it is possible to improve the performance of a hybrid expert system through combining the different diagnosis in a blackboard.
The new *fuge*-method presented above may be used as a knowledge acquisition tool based on Kohonen Networks and therefore may also be used to build an explanation component for hybrid expert systems using Kohonen Networks.

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