Neural networks for the prediction of slope movements

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Summary

The prediction of slope movements is more and more important with increasing land exploitation. As a consequence, prediction models need to be developped for land managment.

Slope movements depend on several factors as erosion or rainfall. Their prediction is always difficult because of the intrinsec variability of governing factors and the complexity of the relationship existing between such factors. Neural networks represent an useful tool establish a relationship between pore pressures and slope displacements. An application concerning the Sallèdes embankment is shortly described in the paper.

1. Introduction

Predicting the occurrence and kinematics of landslides becomes very important with increasing urbanism needs. Prediction models, both mechanical and statistical, need to be developed and included in alarm systems or maintenance programs. Neural networks are considered a promising tool for the prediction of slope movements.

2. What is a neural network

2.1. Storing the knowledge in connections

In its most general form, a neural network is a machine that is designed to model the way in which the human brain performs a particular task: it is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use.

An artificial neural network is an alternative to the sequential «von Neumann» machine, which our computers are based on: This approach consists in establishing a model of the phenomenon to simulate and then in translating it into a set of instructions executed by the machine (computer). This way is excellent if models can be extracted from the observed reality but cannot simulate elementary comportments like objects recognition. To this point one can increase the complexity of formal models or propose an alternative to this method i.e. learning by examples on parallel structures built with simple computing cells, which is named connectionism. In this method the knowledge is acquired by a learning process and is stored in interneurone connection strengths known as synaptic weights. In the former method on the contrary the information is stored in the nodes and the connections are only used for the data transfers.

2.2. Basic model of a neurone

In mathematical terms, we may describe a basic neurone k by writing the following pair of equations

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \tag{1}$$

and

$$y_k = f(u_k - \theta_k) \tag{2}$$

where x_1, x_2, ..., x_p are the input signals and w_{k1}, w_{k2}, ..., w_{kp} are the synaptic weights of neurone k. θ_k is the threshold, $f(.)$ is the activation function and y_k is the output signal of the neurone. In the figure 1, a model of the basic neurone is presented as well as its activation function. This basic neurone, usually called Perceptron can be linked to other similar neurones and interconnected in many ways. They are arranged in layers to build a so-called Multilayered Perceptron (MLP). Usually there are one or two hidden layers and one output layer. Figure 2 shows an example of MLP.

2.3. Learning the network

There are several learning paradigms (supervised, unsupervised, reinforced) using different learning rules (error-correction, hebbian, competitive, boltzmann, etc.) [HAYKIN, 1994]. For function approximation or time series prediction, one usually chooses a supervised learning with a back-propagation algorithm based on the error-correction learning rule. Back-propagation algorithm try to minimise the averaged squared error E, given by:

$$\mathrm{E} = \frac{1}{\mathrm{N}} \sum_{n=1}^{N} \left(\frac{1}{2} \sum_{j=1}^{p} \left(d_j(n) - y_j(n)\right)^2 \right) \tag{3}$$

where p is the number of neurones in the output layer of the network and N is the size of the set of input signals used for learning (the learning set). y_j is the output calculated by the network and d_j is the desired output.

The algorithm calculates the variation of weights by propagating this error from the end of the

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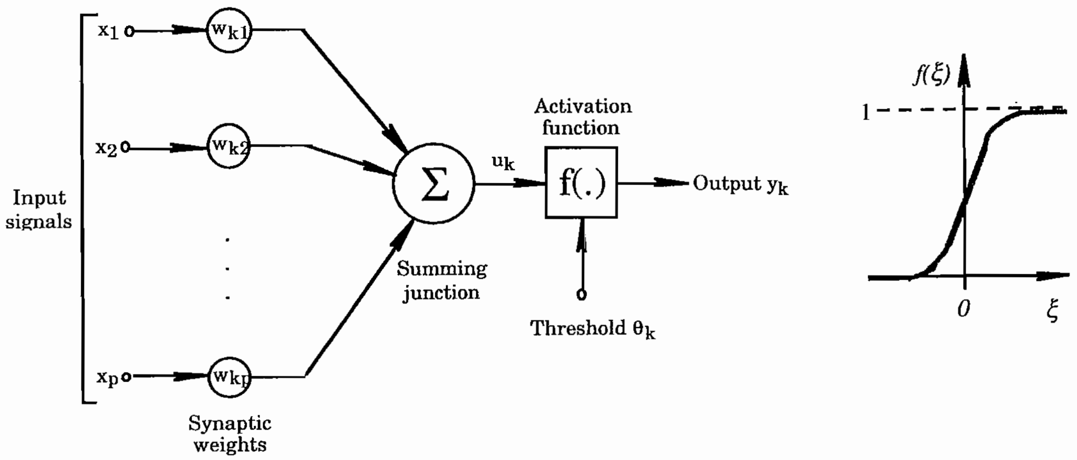

Fig. 1 – Model of a basic neurone k and his non-linear activation function f(ξ).
Fig. 1 – Modello di un neurone base k e la funzione di attivazione f(ξ).

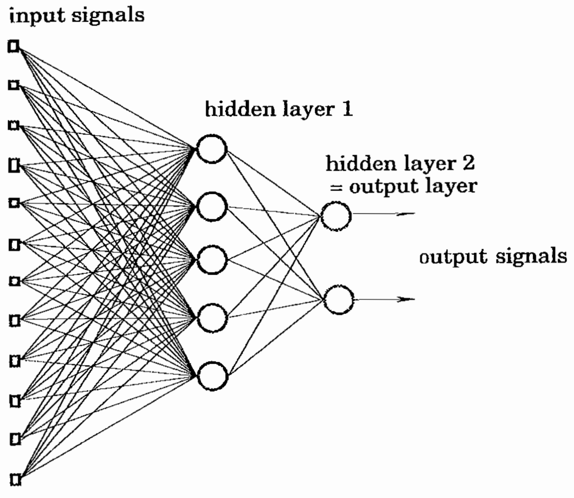

Fig 2 – Example of Multilayered Perceptron (MLP).
Fig. 2 – Esempio di un Multilayer Percepton (MLP).

network. This correction is made after the whole set of input signals is presented to the network and is of the form

$$\Delta w_{ij} = -\eta \frac{\delta E}{\delta w_{ij}} \tag{4}$$

where η is a constant that determines the rate of learning. The use of the minus sign in the equation accounts for gradient descent in weight space. When the algorithm converged, i.e. when the averaged error E is small enough, the weights are fixed and the network can be applied to unknown input signals, which form the test set.

3. Application of neural networks to civil engineering and geomechanics

For a few years several authors have successfully applied neural networks to civil engineering in general and geomechanics in particular. Among these applications of neural networks one can cite the active control of structures subjected to ground excitations or the detection of damages [GHABOUSSI *et al.*, 1995], the determination of constitutive relations in porous media like concrete or sand [GHABOUSSI *et al.*, 1994; ELLIS *et al.*, 1995], or the determination of pile bearing capacity [CHAN *et al.*, 1995; LEE *et al.*, 1996].

It is believed that in the next years a large variety of geomechanical problems will be approached by neural network technology.

4. Use of neural network to predict slope movements

The prediction of slope movements is difficult because the intrinsic variability and the complexity of the governing factors. As a first approximation, it is reasonable to assume a dependence of the movements to pore pressure, rainfalls, and previous movements. As a simplification, the landslide is treated in our case like the movement of one single point.

The neural network is used here as a time series predictor. It is a multilayered Perceptron with a back-propagation learning algorithm and is used in the following way:

– At each time step increment (usually one day) an input signal vector based on values of rainfalls, pore-pressure, velocity or other parameters and functions of them at this time (for example the sum of rainfalls of last two weeks) is built.
– A corresponding desired output signal vector is also built. For our problem this output is the velocity of the landslide.
– The network is then trained on a learning set of data, whose size is about 60-70%o of the whole data set, until the error E defined above is small enough.

- To avoid overfitting, i.e. learning by heart, the network periodically tests during training its weights configuration on a small set called validation test (10% of the data) and learning stops when the error on this set begins to increase.
- The configured network is then applied to the test set (the other 10-20 % of the data), to verify the quality of the learning.

5. The case of Sallèdes

5.1. The site and the data

Sallèdes is now well known as an experimental site of the LCPC to study different problems related to construction on unstable slopes [POUGET *et al.*, 1994].

In this case the parameters considered are rainfalls, evapo-transpiration, pore-pressure and velocity; here the velocity is the angular velocity measured with a fixed inclinometer. The values of the other parameters are given by a pluviometer and piezometer. These instruments are placed in an automatic acquisition central in the middle of the landslide. The time increment is chosen as one day. The whole data set covers a period of one year starting February 25th 1992. This set is divided into three parts: learning, validation and test set (see figure 3 for pore pressure values).

5.2. The network and the results

The network used is a multilayered Perceptron with one hidden layer and an output layer with one neurone. The number of neurones of the hidden layer is determined by trials and a layer with 5 neurones turn out to give the best performance for the convergence of the learning algorithm. Figure 4 gives the configuration of the network.

Figure 5 shows the performance of the network on the test set. The correspondence between the calculated and measured (desired) velocities is quite good; however, since the model predicts the velocity for the next time increment, based on parameters of the last one and two days, it is only a short term prediction.

5.3. Conclusion and perspectives

This example shows the great potential of this model. It compares well with conventional regressive models [POUGET, 1994], but with much less effort since no guessing of the – non linear – regressive model is needed in our case. Nevertheless a careful analysis shows that the network gives a dominant weight to the values of the last one and two days, i.e. the network tries to extrapolate the velocity function by continuity, without having extracted the influence of the other parameters.

For long time prediction, determinant data and functions of these should be found: for example we have shown worthwhile to work with the exponential of the velocity in order to increase the difference between small and large values of it. Another improvement is to reintroduce to the network the computed values of parameters (recurrent network) and to use expert systems to forecast rainfalls for example.

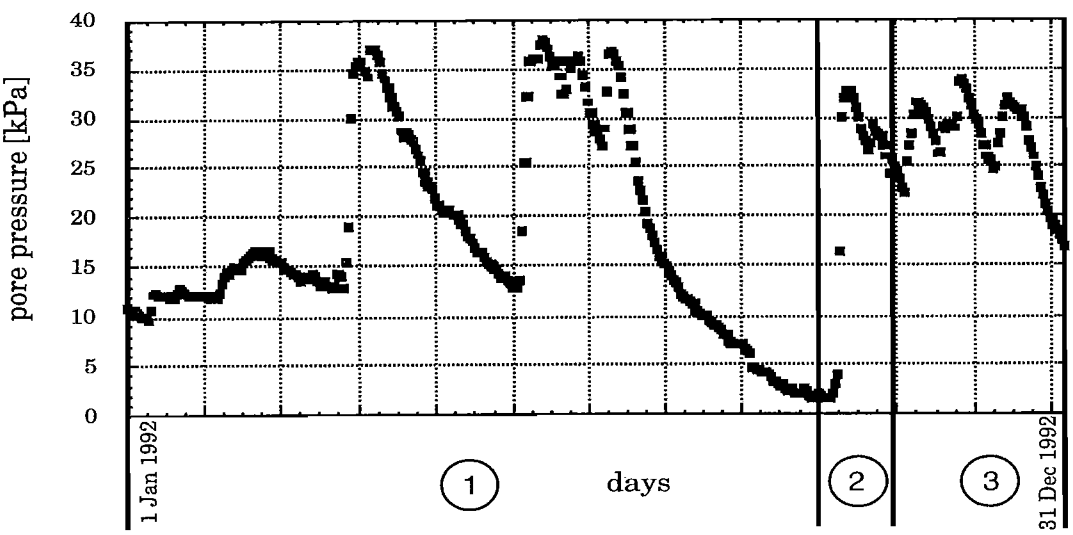

Fig. 3 – Division of the Sallèdes data in three sets. 1 = learning set, 2 = validation set, 3 = test set. (here only the pore pressure as an example).

Fig. 3 – Divisione dei dati di Sallèdes in tre serie: 1 = serie di apprendimento, 2 = serie di convalidazione, 3 = serie di prova (come esempio è riportata la sola pressione neutra).

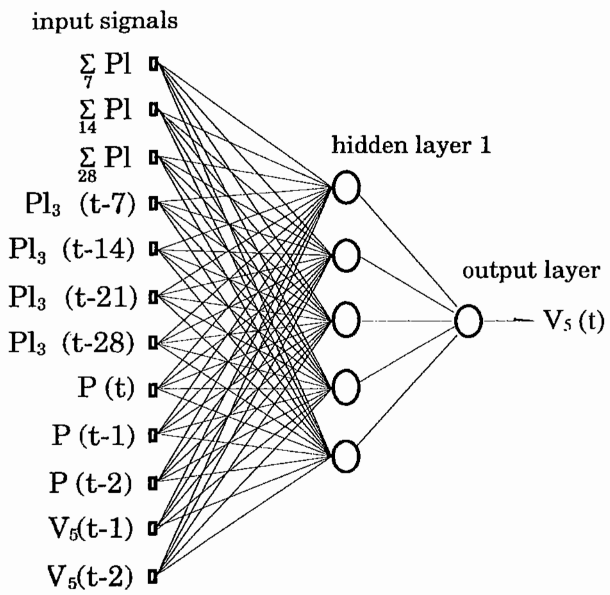

Fig. 4 – Network geometry and inputs for the Sallèdes case (V5 = velocity average on a five days period, P =pore pressure, P13 = rainfalls average on a 3 days period. Pl = rainfalls).

Fig. 4 – Geometria della rete e inputs per il caso di Sallèdes (V5 = media della velocità su cinque giorni, P = pressione neutra, Pl3 = media delle piogge su tre giorni, Pl = piogge).

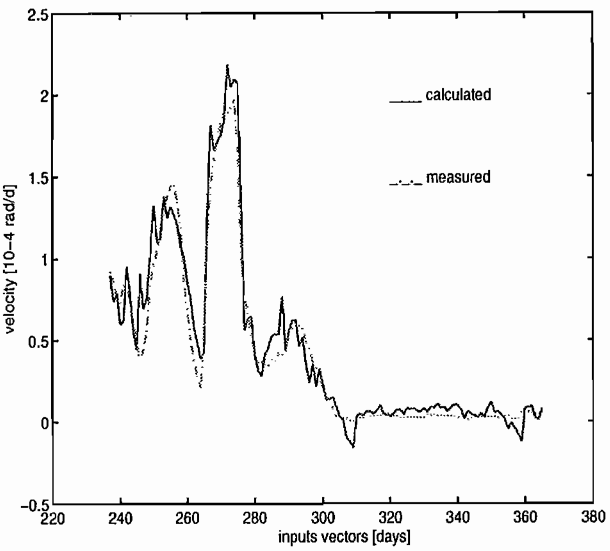

Fig. 5 – Prediction of the velocity for the Sallèdes landslide; mean error 0.13*10–^{4} rad/d (28 % mean velocity).

*Fig. 5 – Previsione della velocità per la frana di Sallèdes; errore medio 0.13*10–^{4} rad/d (28% velocità media).*

6. Conclusion

It is shown that neural networks are already successfully used in geomechanics. It is also shown that they can be an attractive tool for the prediction of slope movements. Further work is being carried out at EPFL to develop and validate the method, and to extend the prediction to larger time period.

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Reti neurali per la previsione dei movimenti di versante

Sommario

La previsione dei movimenti di versante assume una importanza sempre crescente via via che aree sempre più estese vengono utilizzate dall'uomo. Per la gestione del territorio è pertanto necessario sviluppare modelli previsionali.

I movimenti di versante dipendono da numerosi fattori, come ad esempio l'erosione o le piogge. La loro previsione è sempre molto difficile per la variabilità dei fattori in gioco e la complessità delle relazioni esistenti fra questi ultimi. Le reti neurali rappresentano uno strumento molto utile per la definizione di relazioni tra il regime delle pressioni neutre e gli spostamenti indotti. L'articolo descrive una breve applicazione relativa al caso del rilevato di Sallèdes.