Structural Monitoring through Neural Nets

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Abstract

This paper describes the application of neural nets to the management of structural safety at ISMES.

A neural net was developed to deal with monitoring data evaluation, in order to perform heuristic interpretation of the data. The net achieves the same results of symbolic processors previously used, but with reduced development and tuning effort.

1. Introduction

During the last six years the software development unit of ISMES has worked in the field of the artificial intelligence applications to structural engineering, developing knowledge-based systems [1, 2] and neural nets [3, 4] coping with the management of structural safety and the design of dams.

These systems often manage and integrate different kinds of knowledge, such as deep engineering knowledge of physical mechanisms and behaviours (e.g. rotation of a dam), qualitative understanding of phenomena (e.g. congruency relationships among displacements) and heuristic knowledge.

Whilst deep knowledge is usually codified by numerical algorithms, and qualitative reasoning may be implemented by symbolic processing, neural networks seem to be the best choice in many cases when heuristic knowledge is involved.

In this paper, a neural processor is presented, which is able to perform some of the evaluation tasks already carried out by symbolic tools within an existing expert system.

2. The context

ISMES has developed two systems (MISTRAL and KALEIDOS) for the management of the safety of dams and monuments [1,2]. Their task is the interpretation of monitoring data. A part of this task, codifying the shallow knowledge about the structure and the instrumentation, is implemented through empirical rules based on the alarm state of single instruments, taking into account their reliability and significance. Such rules are derived from the analysis of a set of exemplary cases, which allowed to identify weights to be given to the parameters used by the rules.

This process, time consuming and boring for the experts, seemed to be a good field of application for neural networks. Therefore, a neural network was developed to perform the empirical evaluation of data in order to achieve the same results as the symbolic processors previously used, but with reduced development and tuning effort.

The net evaluates the state of the main section of the Ridracoli dam, which has been checked by MISTRAL since 1992; the instruments taken into account by the interpretation system are 3 plumb lines, 3 piezometers and 3 strain gauges.

The *alarm state* of each instrument, as detected by MISTRAL, is the *input* for the net; this is a qualitative value, in a scale of five values, from *normal* to *highly anomalous*, and is codified by integers from 1 to 5, whilst 0 represents missing information about the instrument.

The *output* of the net is the alarm state of the whole section; in the first phase of the research, alarm states generated by MISTRAL were used to train and test the net; training based on evaluations performed by experts will be performed in the near future.

3. Neural nets for interpreting monitoring data

In order to solve the aforesaid problem, an architecture based on a multilayer feed-forward net with backpropagation learning scheme and hyperbolic tangent transfer function was chosen [5].

The net has an input layer of 9 neurons (one for each instrument) and an output layer which includes one neuron (correspondent to the evaluation provided by Mistral).

To determine the number of neurons of the hidden layer we used an algorithm, which is based on the precision of the learning (evaluation of the root mean square between the desired and actual outputs) and on the learning rate (number of presentations of the training set to the net). Initially, a (small) arbitrary number N is chosen and the net is trained; then the number of hidden neurons is doubled and the net trained again; if the behaviour of the net is improved, then the number of neurons is iteratively doubled again, and so on; otherwise the average of the last two values is tried.

For the specific case, a net with 9 hidden neurons provided good results, allowing correct learning of the 93% on the training set and similar results on the test set.

To enhance the learning phase, some nets with larger output layer were trained. An output neuron is associated to each possible output value (that is, 6 neurons, for integer values from 0 to 5), and the output of the net is the integer associated to the neuron with highest activation level.

In such way, the results of the net were enhanced up to 95%.

This architecture could suggest some analogies to the *Radial Basis Function (RBF) Networks* and we plan to experiment them in the near future.

RBF networks are composed of three layers and have a hybrid learning scheme: unsupervised learning between input layer and hidden layer and supervised learning between hidden layer and output layer.

The first learning phase clusters the input cases round some *prototypes* (corresponding to the hidden neurons); the second phase associates each prototype with a *category* or affiliation (corresponding to an output neuron).

3.1. Incomplete information

During the training of the neural nets, indexes with value 0 (lack of information) seemed to cause problems of learning.

In fact, such values are processed in a special way by Mistral, whilst the neural net extends to them its standard interpretation function. Indeed, eliminating some of these cases from the training set allows to enhance the performance of the net up to the 98%.

Other attempts, for instance by forcing large values instead of 0's, were not successful, and confirmed that missing information in the training set is the cause of the problems; a possible solution is the training of specific nets to mime MISTRAL's behaviour with 0's; at runtime, a test on the type of input pattern should drive the selection and activation of the proper net among those previously trained.

3.2. A particular case

Using the training set with complete information (without any 0's), neural nets without the hidden layer achieve very good results (98% of the examples correctly learned).

The results suggest that the function learned by the net is linearly separable; therefore this architecture, similar to the simple perceptron, is proper for the purpose.

However this is a particular case and cannot be generalised.

4. Development environment

The design and training of the networks were performed using NeuralWorks Professional II Plus, whilst pre- and post-processing of data were implemented by FORTRAN programs and a user-friendly interface was developed in Visual Basic.

References

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