Multilayer neural network architecture optimization and performance amelioration for seismic signal classification using genetic algorithms

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ABSTRACT
Artificial Neural Networks ANNs, inspired by the biological neurons in the human brain, are recently showed great results on a variety of classification problems [1]. The main advantage of ANNs is their ability to learn easily and directly complex non-linear mappings from data without requiring mathematical models of the problem. However, the main difficult task in using ANNs is to determine an optimal topology that achieves the best results. Frequently, this task is performed using a trial-and-error process. Nevertheless, this method demands enormous amount of time and effort, and it may not lead to the best performance. Therefore, in this paper, we propose an automatic genetic optimization algorithm for seismic signal classification using the Multilayer Perceptron neural network. This methodology was applied to real seismic data, composed of four classes. The result is an optimized MLP that achieves good performance. Furthermore, the most important thing is the fact that the algorithm searches for the best configuration by testing a large number of configurations without the intervention of the user and in less amount of time, and thus it reduces the designing effort and time compared to the classical method.

DATA
The data used in this work are collected by the local seismic network of Agadir that consists of five stations deployed around Agadir city in Morocco. Each station consists of a velocimeter vertical-component short-period seismometer. Seismic signals are continuously acquired and transmitted in real-time via a radio-frequency FM modulated to the local data center in Agadir city, where they are digitized and analyzed [2] (Figure 1). In addition to earthquake events, numerous other seismograms are recorded on a daily basis, like quarry blasts, wind, ocean waves and cultural activities (Figure 2).

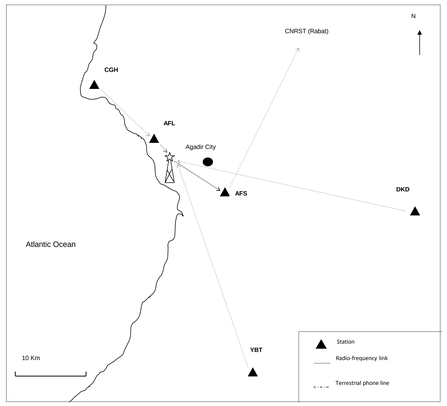

Fig 1. Station location map of the local seismic network of Agadir

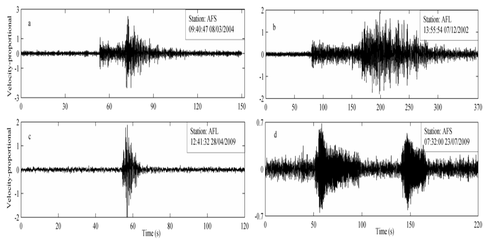

Fig. 2. Vertical component seismograms recorded by the seismic local network of Agadir. (a) local earthquake, (b) regional earthquake, (c) quarry blast, (d) machinery.

FEATURE EXTRACTION
The first step of the classification method is the feature extraction from the seismograms. The feature set used in this work are :

Envelop similarity : measure of similarity between the signal shape *e* of each incoming event and the reference shape e^r determined from explosion events. The envelop similarity E_s is measured using Manhattan distance:

$$E_s = \frac{\sum_{i=1}^{N} |e(i) - e^r(i)|}{\sum_{i=1}^{N} e(i)}$$

Where

$$e(i) = \sqrt{z(i)^2 + HT[z(i)]^2}$$

z(t) is vertical component seismogram, and *HT* indicates the Hilbert Transform.

Duration T_d : defined as the total duration in seconds of the event record from the P wave onset *tp* to the end of the signal *tend* defined as the point where the signal is no longer seen above the noise.

$$T_d = t_{end} - t_p$$

Hour *H* : Day time event distribution reveals that quarry explosions are generally launched between 11:00 a.m. and 02:00 p.m and between 05:00 p.m and 06:00 p.m GMT. Parameter hour *H* can be computed as follows:

$$H = hour + minute/60 + second/3600$$

Spectral centroid S_c : indicates the barycenter of the event spectrum. This measure is obtained by computing the "center of gravity" using the normalized amplitude of FFT envelope weighted by its corresponding frequencies.

$$S_c = \frac{\sum_{i=1}^{N} f(i)e(i)}{\sum_{i=1}^{N} e(i)}$$

e(i) represents the amplitude of the *FFT* envelop of the bin number *i*, and *f(i)* represents its frequency.

Spectral length S_l : is estimated by applying thresholds on its *FFT* envelop.

$$S_l = f_n - f_0$$

where f_0 and f_n are the first and last selected frequency bins.

Skewness *S* : is used here to characterize the degree of symmetry or asymmetry of an event signal around its mean.

$$S = \frac{\frac{1}{N}\sum_{i=1}^{N}(z(i) - \bar{z})^3}{\left(\frac{1}{N}\sum_{i=1}^{N}(z(i) - \bar{z})^2\right)^{3/2}}$$

N is the number of sample in the event signal z and $\bar{z}$ its mean.

CLASSIFIER STRUCTURE
In this study, the most commonly used neural network, called supervised learning multilayer perceptron *MLP* neural network with one hidden layer is considered [3] (figure 3). The data set is divided into three mutually disjoint sets using the hold out method [5] witch are :

- training set, used to adjust the weights of the ANN during its training process.
- validation set, used to stop training and avoid overfitting the data.
- test set, used to evaluate the final classification performance.

Test Confusion Matrix

Output Class \ Target Class	LE	NS	QB	RE	
LE	**18** 21.4%	**0** 0.0%	**3** 3.6%	**1** 1.2%	81.8% 18.2%
NS	**1** 1.2%	**28** 33.3%	**0** 0.0%	**0** 0.0%	96.6% 3.4%
QB	**1** 1.2%	**0** 0.0%	**22** 26.2%	**0** 0.0%	95.7% 4.3%
RE	**0** 0.0%	**0** 0.0%	**0** 0.0%	**10** 11.9%	100% 0.0%
	90.0% 10.0%	100% 0.0%	88.0% 12.0%	90.9% 9.1%	92.9% 7.1%

Fig. 4. Confusion matrix of the MLP neural network achieved by the GA.

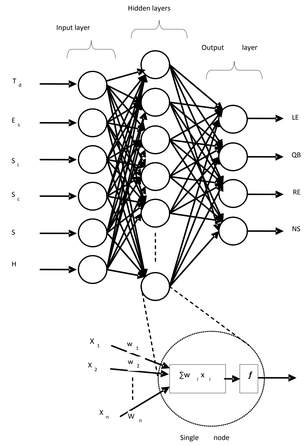

Fig. 3. Architecture of the multilayer perceptron neural network used to classify seismic events.

RESULTS AND DISCUSSION
To choose the best classifier topology and evaluate its performance, a data set of 343 event seismograms was chosen and classified by seismic analysts. These seismograms are distributed among the four classes. These are: noise (NS), local earthquake (LE), regional earthquake (RE) and quarry blast (QB).
After seismogram processing, the six input features were extracted.
A genetic algorithm with the chromosome illustrated by figure 5 is used to choose the best classifier [4].
The genetic algorithm is showed in figure 6.
The parameters coded by the chromosome are more detailed by tables 1 and 2.
The GA is running until the best classifier is found which corresponds to the maximum value of fitness function (figure 7). The performance of the selected MLP is shown in figure 4.

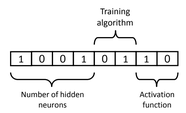

Fig. 5. chromosome coding for the genetic algorithm

Table 1. Activation function coding in the GA chromosome

Chromosome code part	Activation function	Description
00	logsig	Logarithmic sigmoid transfer function
01	radbas	Radial basis transfer function
10	satlin	Saturating linear transfer function
11	tansig	Hyperbolic tangent sigmoid transfer function

Table 2. Training function coding in the GA chromosome

Chromosome code part	Training function	Description
00	traincgf	Conjugate gradient backpropagation with Fletcher-Reeves updates
01	trainlm	Levenberg-Marquardt optimization
10	trainrp	resilient backpropagation algorithm
11	trainscg	Scaled conjugate gradient backpropagation

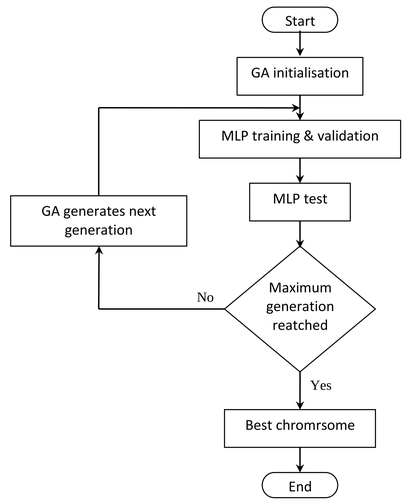

Fig. 6. Genetic algorithm For choosing the best MLP classifier.

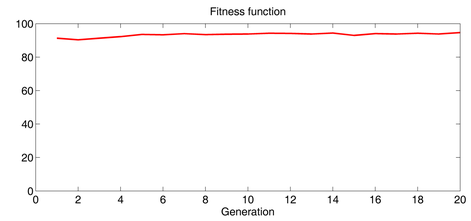

Fig. 7. Fitness function as a function of the Generation.

CONCLUSION
The Multilayer Perceptron neural network combined with a genetic optimization algorithm has showed its capability to determine automatically an optimal topology of the classifier that achieves the best results in seismic signal classification. The result is an optimized MLP with good performance and capability of reducing the designing effort and time compared to the classical method.

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