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Seismic noise filtering based on Generalized Regression Neural Networks

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ABSTRACT

This paper deals with the application of Generalized Regression Neural Networks to the seismic data filtering. The proposed system is a class of neural networks widely used for the continuous function mapping. They are based on the well known nonparametric kernel statistical estimators. The main advantages of this neural network include adaptability, simplicity and rapid training. Several synthetic tests are performed in order to highlight the merit of the proposed topology of neural network. In this work, the filtering strategy has been applied to remove random noises as well as source-related noises from real seismic data extracted from a field in the South of Algeria. The obtained results are very promising and indicate the high performance of the proposed filter in comparison to the well known frequency–wavenumber filter.

1. Introduction

A fundamental problem of seismic data processing is to effectively remove noise while preserving primary reflections which constitute the medium of the information about the subsurface structure. This noise occurs at all stages of seismic imaging, starting from data acquisition through to the final stage of processing. Noise effects can be extremely undesirable; it can not only decrease the performance of seismic data processing (velocity analysis, seismic deconvolution, and migration process), but can also lead to subsequent erroneous interpretation (it creates a fictive geologic structure in the seismic section after stack) (Henry, 1997; Mari and Glangeaud, 2001).

The complexity of noise removal problems depends on the type of the noise corrupting the recorded data. The most common types of noise come from various sources, such as wind motion, poorly planted geophones, or electrical noise (Cassano and Rocca, 1973; Buttkus and Bonnemann, 1999) which are known as random noise. Note that some of these seismic random noises invariably exhibit spike-like characteristics (Ferahtia et al., 2010). The other category includes coherent noises like multiples.

Seismic noise attenuation methods encountered in the literature can be divided broadly into two categories depending on the characterization strategy used to identify and remove these noises: filtering methods and modelling methods. Filtering methods identify features that differentiate noise from signal. These methods require reliable criteria to discriminate useful signal from noise. In general, such criteria cannot be derived easily (Djarfour et al., 2008). Modelling methods first predict noise characteristics and then subtract noise from the data. The success of noise modelling depends on restrictions to a model with simplified hypotheses, so the efficiency of this strategy decreases when these hypotheses cannot be satisfied (Mari and Glangeaud, 2001).

The performance of different strategies deteriorates rapidly when signal-to-noise ratio decreases. Moreover, removing noise using both filtering and modelling may alter considerably the signal component during the elimination of the noise, due to the weak discrimination between these two components (Henry, 1997; Buttkus and Bonnemann, 1999). In spite of significant made progress regarding the performance of the proposed filters, yet reducing the noise completely either from synthetic or real data is still not achieved (Cassano and Rocca, 1973; Mari and Glangeaud, 2001; Ferahtia et al., 2010). So far, there is no noise attenuation technique that works universally in all noise types. Therefore, recognizing and attenuating the noise remains one of the greatest challenges and increasingly getting more complicated in signal processing. In order to identify and reduce noise, and hence improve the quality of seismic data, it has become more than a demanding issue for developing reliable and powerful filtering tools.

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The method presented in this paper is an attempt to remove seismic noise using the Generalized Regression Neural Networks (GRNNs). The GRNN has remarkable ability to derive meaning from highly corrupted data and/or imprecise data. The method's potential has been proved in several applications such as image processing (Chaofeng et al., 2011), dynamical systems (Chen and Chen, 1995) and seismic filtering (Djarfour et al., 2008). The design of this artificial neural network (ANN) is based on learning from examples, which will be used to acquire important information to recognize and attenuate random and source-related noise in seismic data.

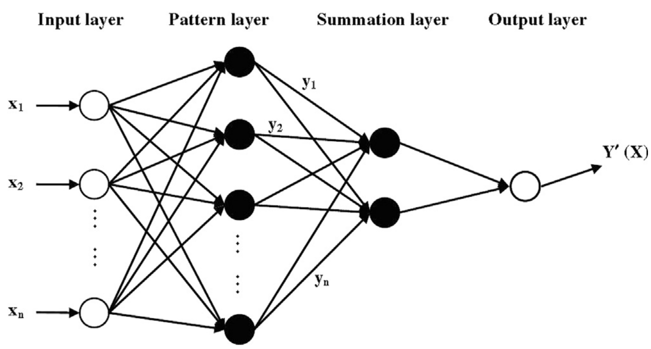

Fig. 1. GRNN topology.

2. Seismic data filtering

The presence of noise in seismic data affects the signal-to-noise ratio, obscures details, and decreases the accuracy of dynamic and static corrections, thus degrading final data quality, and complicates identification of useful information (Henry, 1997).

Eq. (1) represents a simple model for a reflected seismic signal (Henry, 1997; Mari and Glangeaud, 2001):

$$T(t) = W(t) \ast R(t) + B(t) \tag{1}$$

where $\ast$ represents the convolution operator, $T(t)$ is the observed seismic signal, $W(t)$ is the source seismic signal, $R(t)$ represents the reflectivity operator (unknown to be extracted), and $B(t)$ is the seismic noise. In this context, "natural" noise is generated from physical wave propagation effects and "artificial" noise is generated by recording or processing of the seismic data; these two types of noise can be coherent or random.

The filter design process estimates a filter operator such that convolution of the filter operator with the observed seismic signal, $T(t)$, results in the best estimate of $W(t)^*R(t)$. All the conventional techniques for noise attenuation fundamentally require a priori information on characteristics of signal and noise. This information is usually not well known and the parameters that characterize the signal and noise can often be estimated inaccurately.

In this study, we will integrate a Generalized Regression Neural Network in the seismic data processing sequence to filter noise from the seismic data.

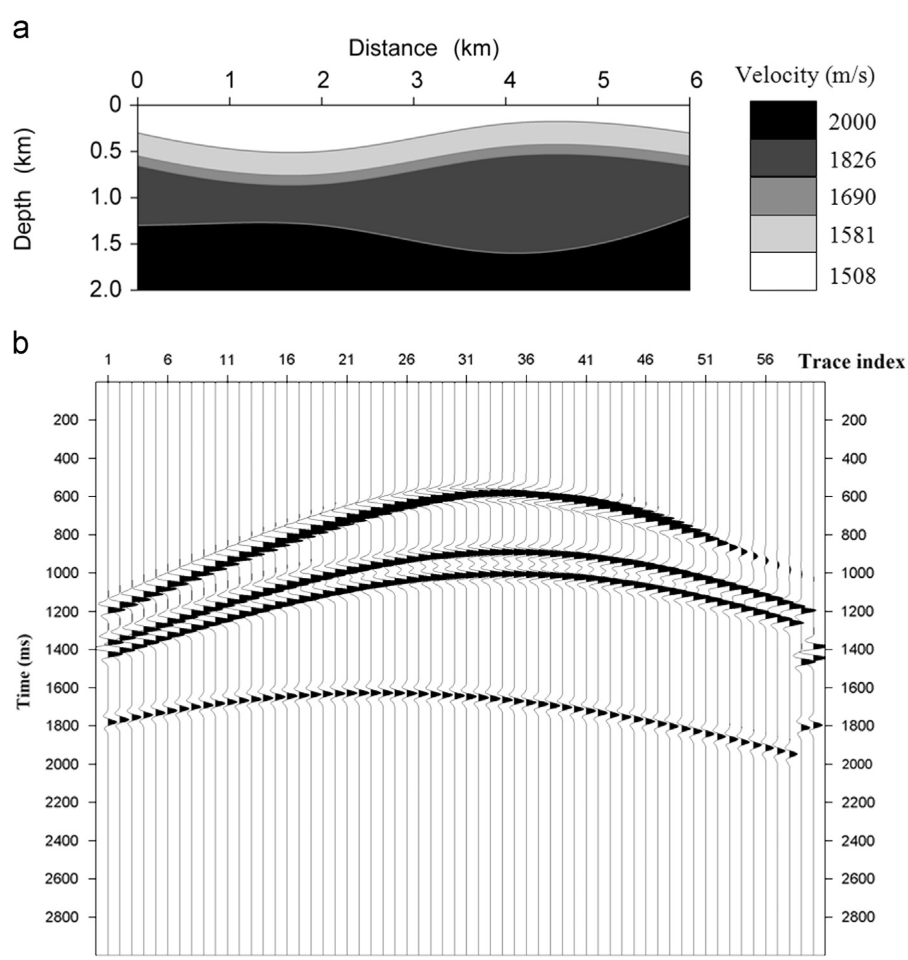

Fig. 2. (a) Subsurface model used to create the synthetic data. (b) Noise-free synthetic shot gather used during synthetic application. The model and shot gather were created using the free software Seismic Unix (SU).