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Earthquake prediction in seismogenic areas of the Iberian Peninsula based on computational intelligence

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ABSTRACT

A method to predict earthquakes in two of the seismogenic areas of the Iberian Peninsula, based on Artificial Neural Networks (ANNs), is presented in this paper. ANNs have been widely used in many fields but only very few and very recent studies have been conducted on earthquake prediction. Two kinds of predictions are provided in this study: a) the probability of an earthquake, of magnitude equal or larger than a preset threshold magnitude, within the next 7 days, to happen; b) the probability of an earthquake of a limited magnitude interval to happen, during the next 7 days. First, the physical fundamentals related to earthquake occurrence are explained. Second, the mathematical model underlying ANNs is explained and the configuration chosen is justified. Then, the ANNs have been trained in both areas: The Alborán Sea and the Western Azores–Gibraltar fault. Later, the ANNs have been tested in both areas for a period of time immediately subsequent to the training period. Statistical tests are provided showing meaningful results. Finally, ANNs were compared to other well known classifiers showing quantitatively and qualitatively better results. The authors expect that the results obtained will encourage researchers to conduct further research on this topic.

1. Introduction

The seismicity in the Iberian Peninsula is characterized by the predominance of moderate magnitude earthquakes. Large earthquakes happen after long periods of time and the seismicity is spread over large areas. The seismicity is caused by the convergence directed NW–SE between Eurasia and Africa's plates. In this study, the seismogenic areas defined by Morales-Esteban et al. (2010) are used.

The challenge of finding a successful method to predict earthquakes has been faced for over 100 years (Geller, 1997). An earthquake prediction should state, according to Allen (1982): When, where, how big and how probable the next earthquake is going to be. Despite the great effort made and the multiple models developed by different authors (Tiampo and Shcherbakov, 2012), no successful method has been found yet. Due to the random behavior of earthquakes generation, it may never be possible to ascertain the exact time, magnitude and location of the next damaging earthquake.

Neural networks have been successfully used for solving complicated pattern recognition and classification problems in many domains such as financial forecasting, signal processing, neuroscience, optimization, etc. (in Adeli and Panakkat (2009) neural applications are detailed). But only very few and very recent studies have been published on the application of neural networks for earthquake prediction (Alves, 2006; Madahizadeh and Allamehzadeh, 2009; Panakkat and Adeli, 2009; Srilakshmi and Tiwari, 2009).

In this study Artificial Neuronal Networks (ANNs) are used to predict earthquakes. An ANN can be defined as a computing system made up of simple, highly interconnected processing elements, which processes information by their dynamic state response to external inputs. ANNs are typically organized into layers. The layers consist of a number of interconnected nodes which contain an activation function. Patterns are presented to the network via the input layer, which communicates one or more hidden layers where the actual processing is done through a system of weighted connections. The hidden layers, then, link to an output layer where the answer is the output. Most ANNs contain certain types of learning rules which modify the weights of the connections according to the input patterns they are exposed to.

The application of ANNs to earthquake data is proposed in this work to provide two kinds of prediction:

(1) The probability of an earthquake of magnitude equal or larger than a preset threshold, during the next 7 days, to happen in any of the seismogenic areas subjected to analysis.
(2) The probability of an earthquake of a limited magnitude interval to happen, during the next 7 days, in any of the seismogenic areas subjected to analysis.

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Therefore, the ANN-based method here presented meets the requirements demanded for earthquake prediction: When, during the next 7 days; where, applied to two different seismogenic areas of the Iberian Peninsula; how big and how probable, the probability of an earthquake of magnitude equal or larger and in a limited magnitude interval to happen is given for every studied area. It is worth noting that the method introduced in this study has been adjusted to generate as few false alarms as possible. Moreover, the performance of the proposed method has been compared to several well-known machine learning algorithms, outperforming the results obtained by them in the two areas analyzed.

The rest of the work is divided as follows. Section 2 reviews the existing methods used to predict the occurrence of earthquakes. The geophysical fundamentals are described in Section 3. A description of the ANNs used in this work as well as its mathematical fundamentals is provided in Section 4. On the other hand, in Section 5, the training of the ANNs is explained together with the method to evaluate the networks. In Section 6, the results obtained for every ANN in the testing process are shown. Finally, Section 7 summarizes the conclusions drawn.

2. Related work

There is no general agreement among researchers on how to build earthquake forecasting models so far (Field, 2007). Hence, different kinds of approach to extract knowledge have been proposed during the last decade. A thorough survey recently published (Tiampo and Shcherbakov, 2012) divides these techniques into two categories, admitting some overlap between them: Those that use strategies to identify particular physical processes and those based on smoothing seismicity. As this work proposes the integration of physical processes as input for the ANN's, only works based on this category are reviewed in this section. In particular, three main groups of techniques are explored. First, methods incorporating statistical data of physical processes; second, studies focused on variations of the Gutenberg–Richter law's *b*-value; third, methods that use machine learning.

The Regional Earthquake Likelihood Models (RELM) project of the Southern California Earthquake Center (SCEC) has published many different prediction models for Southern California since its foundation in 2000, based on observed physical processes. Under the umbrella of RELM, the U.S. Geological Survey (USGS) and the California Geological Survey (CGS) developed a time-independent model assuming that earthquakes' occurrence probability follows a Poisson distribution (Petersen et al., 2007). The authors also presented a time-dependent approach based on the national seismic hazard model, including some additional recurrence information.

Kagan et al. (2007) produced a five-year forecast of earthquakes with magnitudes 5.0 and above for Southern California. This method was based on spatially smoothed historical earthquake catalog (Kagan and Jackson, 1994) and its main feature lied on observing regularities in earthquake occurrence. A model based on similar assumptions can be found in Helmstetter et al. (2007).

The authors in Shen et al. (2007) suggest a probabilistic forecast based on geodetically observed strain rate averaged over approximately ten years. The occurrence rate is assumed to be proportional to the strain rate, which is considered as an intermediate-term earthquake predictor. The model proposed by Bird and Liu (2007) is based on simple hypothesis for predicting long-term shallow seismicity from plate tectonics theory. They compute a long-term forecast from a kinematic model of neotectonics. Alternatively, Console et al. (2007) created an earthquake clustering model assuming that every earthquake is potentially a main shock with its own aftershock sequence decaying according to the modified Omorilaw, or the real state model, or can be regarded as triggered by previous events. The magnitude distribution is obtained from the Gutenberg-Richter law.

Rhoades (2007) shows a method based on the EEPAS model (Every Earthquake a Precursor According to Scale) that uses previous minor earthquakes of the catalog to forecast the major ones. This model adopts predictive scaling relation derived empirically from examples of the precursory scales increase phenomenon. He produces long-term forecasting of earthquakes of magnitude $M \geq 5.0M_s$ for Southern California. Moreover, Ebel et al. (2007) present a long-term forecast map, of $M_s \geq 5.0$ earthquakes, based on the extrapolation into the future of the average rates from the past of $M \geq 5.0M_s$ mainshocks, in the forecast area. They also produce two short-term (one day) methods based on the observation that mainshocks in California and western Nevada of $M \geq 4.0M_s$ are more temporally clustered than expected. Meaningful is the work developed by Ward (2007) who contributes with five different methods based on geodesy, geological, historical seismicity, and computer simulations of earthquakes.

Equally remarkable is the work in Wiemer and Schorlemmer (2007) that proposes a quasi-stationary earthquake likelihood model for California based on the assumption that small-scale (5–15 km) spatial variations in *b*-value of the Gutenberg–Richter law are meaningful for future forecasting seismicity. The *b*-value is supposed to be inversely dependent of applied shear stress so it can be used as a stress meter within the Earth's crust. This model is known as the Asperity-based Likelihood Model (ALM) and considers that the *b*-value of recent micro-earthquakes is the most important information for forecasting future events of magnitude $M \geq 5.0M_s$.

The method presented in Tiampo et al. (2002) uses pattern dynamics to historical seismicity data revealing that systematic variations in seismicity prior to recent earthquakes can be observed in Southern California. The results obtained show that seismic activity is highly correlated across many space and time scales within large volumes of the Earth's crust. Moreover, the paper in Holliday et al. (2007) is based on the Pattern Informatics (PI) method that identifies regions that have systematic fluctuations in seismicity. This method is not an earthquake prediction but a forecast of where future earthquakes are expected to occur within the next 5 to 10 years. Similarly, the method proposed in Nanjo et al. (2006) applied a modified PI method to forecast the location of future larger events in central Japan based on analyzing the space time patterns of past earthquakes to find possible locations where future larger events are expected to occur. Later, Toya et al. (2010) expands the PI approach to forecasting earthquakes into the vertical dimension. This method is particularly advantageous over 2D analysis in resolving vertical overlapped seismicity in highly complex tectonic environment. The authors in Gerstenberguer et al. (2007) have developed a methodology to spatially map the probability of earthquake occurrence in the next 24 h.

Many studies have been developed about the temporal variations of the *b*-value and some of them relating the *b*-value to earthquake prediction, like Morales-Esteban et al. (2010), Patanè et al. (1992), Wiemer and Benoit (1996), Wiemer and Schorlemmer (2007) Wiemer et al. (2002) and many others. There is still some controversy among investigators about the spatial and temporal variations of the *b*-value. It is important to know how the sequence of *b*-values has been obtained, before presenting conclusions about its variation.

Thus, the work in Nuannin et al. (2005) deeply studied earthquakes in the Andaman–Sumatra region and demonstrated that earthquakes are usually preceded by a large decrease in *b*-value, although in some cases a small increase in this value preceded the shock. Moreover, Sammonds et al. (1992) have shown that large earthquakes are often preceded by an intermediate-term increase in *b*-value, followed by a decrease in the months to weeks before the earthquake. The studies in Gibowitz (1974) and Wiemer and Wyss (2002) on the variation of the *b*-value over time refer to aftershocks. The authors concluded that the *b*-value is a stress-meter that depends inversely on differential stress (Gulia and Wiemer, 2010; Nuannin et al., 2005; Schorlemmer et al., 2005).

Wiemer and Wyss (2002) have demonstrated that statistically significant variations for the *b*-value happen in various tectonic regimes on local to regional scale. While there is evidence for spatial variability