Paper:

Artificial Neural Networks for Earthquake Anomaly Detection

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Earthquakes are natural disasters caused by an unexpected release of seismic energy from extreme levels of stress within the earth's crust. Over the years, earthquake prediction has been a controversial research subject that has challenged even the smartest of minds. Because numerous seismic precursors and other factors exist that may indicate the potential of an earthquake occurring, it is extremely difficult to predict the exact time, location, and magnitude of an impending quake. Nevertheless, evaluating a combination of these precursors through advances in Artificial Intelligence (AI) can certainly increase the possibility of predicting an earthquake. The sole purpose for predicting a seismic event at a pre-determined locality is to provide substantial time for the citizens to take precautionary measures. With this in mind, Artificial Neural Networks (ANNs) have been promising techniques for the detection and prediction of locally impending earthquakes based on valid seismic information. To highlight the recent trends in earthquake abnormality detection, including various ideas and applications, in the field of Neural Networks, valid papers related to ANNs are reviewed and presented herein.

Keywords: artificial neural networks, ANN, earthquake anomalies detection, precursor, earthquake prediction

1. Introduction

An earthquake is a natural disaster caused by an unexpected release of seismic energy due to extreme stress within the earth's crust. Such energy is released because of aggressive movements of the tectonic plates in active fault zones. The accumulated energy, containing immense pressure, is transferred from the earth's crust to its surface in the form of seismic waves. These waves can either roll or travel parallel to the surface causing the destruction of anything that falls within its path. Earthquakes can create severe structural damages, irretrievable financial ruin, and irrecoverable loss of human life.

Over the years, earthquake prediction has been a controversial subject that has challenged even the brightest researchers. Because numerous seismic precursors and other factors indicating a potential earthquake exist, it is extremely difficult to predict the exact time, location, and magnitude of an impending quake. Nevertheless, evaluating a combination of these precursors through advances in Artificial Intelligence (AI) can increase the possibility of an earthquake prediction.

In this direction, Neural Networks (NNs) have been utilized to translate seismic information and provide a valid detection and prediction of locally impending earthquakes. A Neural Network is an AI method inspired from the functionality of the human brain. A NN consists of interconnected neurons, weights, links, activation functions, and a training set through which the system "learns" from experience by corresponding with output errors [1]. The accuracy of NNs predictions depends highly on the network's output uncertainties; a network adjusts itself using provided learning method to minimize output errors [2]. NNs have the aptitude to deduce patterns and detect trends that are nearly impossible for humans to recognize, and hence are a valuable commodity for detecting seismic activity.

For example, on February 4, 1975, a 7.3 magnitude earthquake struck the city of Haicheng in Northeast China, resulting in over 2,041 casualties, leaving thousands of people homeless, and destroying various structures in its path [3]. Chinese officials confirmed that an earthquake warning was announced only hours before the main shock occurred [4, 5]. The impending earthquake was successful predicted based on various seismic precursors observed by seismologists and other scientists [6]. The most important precursor was a sequence of foreshocks, although other precursors such as abnormal animal behavior, radon activity, changes in land and ground water elevations, and altered chemical properties each played a vital role prior to the evacuation [4, 6]. This specific case shows that earthquakes may provide multiple precursors. When these different precursors are integrated through an NN analogy, they can increase the probability of predicting earthquakes with a higher accuracy [7].

This paper describes background information on earthquake properties, and surveys the scientific possibilities of earthquake prediction using NNs. In addition, this survey provides a detailed layout of different seismic precursors such as peak ground acceleration, liquefaction, radon detection, and aftershocks. Moreover, this paper discusses how these seismic precursors are utilized by NN computations for earthquake prediction and detection. A respective network analysis is presented for each type of seismic precursor, along with the type of NN used. In addition, a detailed explanation of the objective of the network, a description of its input and output neurons, and a review of the training and testing phases are provided. Finally, this paper surveys recent trends in detecting earthquake abnormalities and current NN applications for seismic prediction.

2. Strong Ground Motion Analysis as a Seismic Precursor

Strong ground motion is a sudden violent tremble on the surface of the earth that occurs before an imminent earthquake. Seismic instruments such as accelerometers are widely used in earthquake-prone areas to monitor and collect such data. Located approximately 30 m below the surface of the earth, accelerometers are among the most essential tools used to acquire input parameter readings for various types of ground motion analyses [8]. However, as one of the many tools providing impending earthquake information, accelerometers are ineffective as primary tools for seismic detection because they only observe vibrations at high frequencies. Over the years, ground motion prediction using various NN approaches and methodologies has been a highly reviewed subject. Idriss [9] conducted an extensive ground motion analysis using related content periodically collected until 1978. Boore and Joyner [10] followed up by incorporating important ground motion prediction equations in 1981; their studies laid the foundations for earthquake prediction using a network analogy. Later, Campbell [11] conducted a wider range of ground-motion analyses up to 1985 that contained vital equations and innovative precursory analogies.

In this section, we blend critical ground motion applications into network architecture to increase the likelihood of a strong ground motion prediction. The ground motion applications taken into consideration as precursors to an earthquake are a Peak Ground Acceleration (PGA) and the potential liquefaction. The following subsection features a thorough survey on various approaches to predicting a PGA and the possibility of liquefaction using ANNs.

2.1. Predicting Peak Ground Acceleration Using Artificial Neural Networks

A PGA is a measure of earthquake acceleration with respect to extensive ground-shaking movements [12]. As a seismic precursor, a PGA is induced through an intense release of energy from an earthquake, causing ground deformations such as liquefaction, landslides, and surface fault ruptures [13, 14].

Derras and Bekkouche [15] introduced a comprehensive approach to estimating the maximum PGA using a Feed-forward Back-propagation Neural Network (FFBP-ANN). The outcome of the network was then compared to two Ground Motion Prediction Equations (GMPE) mod-

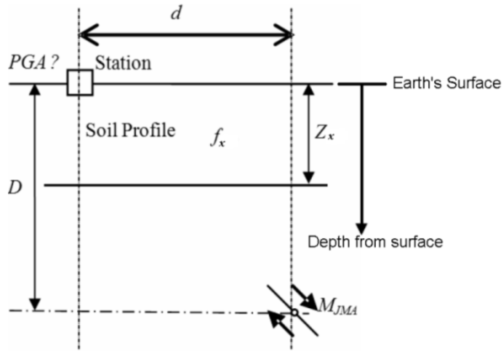

Fig. 1. Indicated site seismic parameters utilized in a PGA evaluation.

eled by Ambraseys and Takahashi [15], respectively. The GMPE models were used as an alternative approach for the estimation of the PGA values where accelerometric monitoring stations are not present. Such an approach requires a large volume of data on the site coefficients as well as pre-recorded PGA values. In return, the GMPE theory has been observed to be relatively weaker in terms of prediction compared to an FFBP-ANN owing to its inability to cope with non-linear expressions and complex data types. An FFBP-ANN was designed with a total selected set of 1,000 epochs and a tangential-hyperbolic sigmoid/linear activation function, and consists of five input parameters: the locally measured meteorological agency magnitude, the depth of focus at which an earthquake is triggered, the epicenter distance, the thickness of the sedimentary layers (Z_x), and the corresponding resonant frequency (f_x). Importantly, both the sedimentary thickness and the resonant frequency have a constant shear wave velocity of $x = 800$ m/s, as depicted in [16]. **Fig. 1** [15] provides a visual representation of the site parameters utilized for evaluation.

The ANN configuration utilized in **Fig. 1** consists of 326 training and 1,850 testing records extracted from KiK-net data. A comparison between an FFBP-ANN, Ambraseys's GMPE model, and Takahashi's GMPE model shows that the performance of the NN (FFBP-ANN) is far superior to the two GMPEs. The coefficient of determination (R^2) for the PGA estimated by an NN is 0.94 as compared to those of the GMPE approaches, which are 0.76 and 0.82, respectively. In the same venue, the NMRSE for the NN approach is considerably smaller, at 0.11%, as compared to the GMPE models, which shows a respective NMRSE of 0.25% and 0.17% confirming that a PGA approximation using an NN surpasses that of the GMPE models in terms of both performance and accuracy. Specifically, the results show that the epicentral distance parameter heavily influences the outcome of the PGA value, obtaining the best R and MSE values of 0.51/0.48 and 0.075/0.076 for the training and testing phases, respectively. In contrast, the focal depth and site parameters have the least influence on the outcome of the PGA value. Furthermore, a combination of all five parameters is observed to return the optimal results, retaining an $R - score$ of 0.85 and 0.84, and an MSE value of 0.0203