Supplementary Material

Can spiking neural networks predict earthquakes?

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If a potential disaster can be averted, lives can be saved and losses avoided. Risk mitigation strategies from health to civil defence often depend on simple models using a few variables based on limited data. Accurate prediction of future events seems to be the stuff of fantasy. But recent advances in machine learning offer the intriguing possibility that disastrous events, as diverse as strokes, earthquakes, financial market crises, or degenerative brain diseases, could be predicted early if the patterns hidden deeply in the intricate and complex interactions between spatial and temporal components could be understood [1-6]. Although such interactions are manifested at different spatial or temporal scales in different applications or domain areas, the same information-processing principles can be applied. A large amount of spatio-temporal or spectro-temporal data (SSTD) is now available. A radically new approach to modelling such data can enable faster and significantly better machine learning and pattern recognition, offering the realistic prospect of much more *accurate* and *earlier* event prediction, and to a much better understanding of spatio-temporal causal relationships.

Researchers have recently demonstrated that third-generation artificial neural networks, called spiking neural networks (SNN), can be used to learn patterns in SSTD [5-16]. In SNN, information is represented and processed as temporal sequences of spikes, similar to the way the brain processes information. Information is represented as electrical potentials, considered as binary events – spikes – that form temporal sequences transferred between spatially distributed neurons. Like the brain, SNN learn from data related to certain events by forming and updating connections between neurons, creating neuronal chains and networks. Moreover, a chain may be incrementally activated when only a small amount of new data is presented [7]. Hence, SNN are capable of fast parallel information processing, compact representation of space and time, learning, and pattern recognition [16-25]. Highly parallel neuromorphic hardware systems of SNN that comprise thousands or millions of computational neurons are now available [26-32].

One of the intriguing possibilities opened up by SNN is the potential to use them to analyse seismic data to predict earthquakes. Forecasting severe earthquakes, that is, assigning a probability to a general earthquake hazard in a region over a period of years or decades, is undertaken routinely and forms an important part of public education and preparedness in seismically active countries. But *predicting* earthquakes is highly controversial. It is considered by many scientists to be impossible, and by others to be at best an immature science. Nonetheless, some recent studies have suggested that there are certain signatures in the seismograms that could be used to predict earthquakes, such as using the high frequency component of microseismic noise readings [33], or pulsed vibrations [34], or other anomalies [35-36]. Copious amounts of seismic data are produced every second by thousands of seismographs installed in seismically active places, from Turkey to Tonga. There is potential, then, to apply computational intelligence methods to seismographic data to see whether major earthquakes can be predicted. Over the past five years, several promising new techniques have been tried.

Researchers in Chile have used artificial neural networks to predict earthquakes, using fundamental laws in geophysics to extract the input features from the available time-variant data. The same authors used a similar technique to study earthquake data from sites around the Iberian Peninsula [37-38]. An alternative approach, using an adaptive neural fuzzy inference system (ANFIS), was proposed in 2011 by Shibli [39]. This used the location of the earthquake as the input and the magnitude as the output. Subsequently, Zamani *et al* proposed an alternative ANFIS approach, disaggregating historical earthquake data into two kinds of input, spatial and temporal, with different processing techniques and separate analysis [40]. Previously, Joelianto *et al* had used an inference system to predict a time-series of earthquake parameters for the Sunda region of Indonesia [41]. Recently Ikram and Qamar [42] have used rule-based data mining.

Several computational intelligence approaches have extracted features from earthquake records of a particular region to predict aftershocks (smaller earthquakes happening hours to weeks after a major event), using empirical relations from geophysics such as the b-value (Gutenberg-Richter Law), Båth's Law, and Omori's Law. But a research team in New Zealand has used multiple time-series readings of seismic activity *prior* to the earthquake, applying a SNN architecture called NeuCube [19,20]. Although NeuCube was designed to map and model brain signals, it has proved to be useful for various non-brain case studies, such as predicting an individual occurrence of stroke few days ahead of the event using a combination of medical risk factors and environmental variables [22].

Can major earthquakes be predicted using SNN? In a preliminary experiment, we have used seismometer readings from the GeoNet web services, provided by GNS Science, New Zealand [43] (Fig.1a). We have built NeuCube models and tested their predictive accuracy on retrospective events in the Christchurch region of New Zealand (Fig.1b). The region experienced major earthquakes between 2010 and 2015. Changes in seismic data over time from 52 sites in New Zealand are encoded into trains of spikes [19-22]. Then the SNNcube is trained so that spatially located neurons representing the spatial locations of seismic sites are connected if there is a temporal seismic relationship between the sites (Fig.1 c-g). The NeuCube models predict severe earthquakes with remarkable accuracy, ranging from 75% 24 hours before the event, to 85% 6 hours before, and 91.36% 1 hour before. A trained SNN cube represents a dynamic and transparent model of seismic activities that can be further studied for a deeper understanding of the dynamic seismic processes, as explained in this case study, Fig.1c-g.

Such developments show that SNN can be successfully used for early and accurate prediction of hazardous events. The models still need to be verified using large-scale global earthquake data from seismic monitoring sites around the world, and some fine-tuning will be needed to find the best prediction horizon and observation period. Nonetheless, this is a promising line of research for hazardous event prediction, with great potential to understand geophysical phenomena - and save lives.

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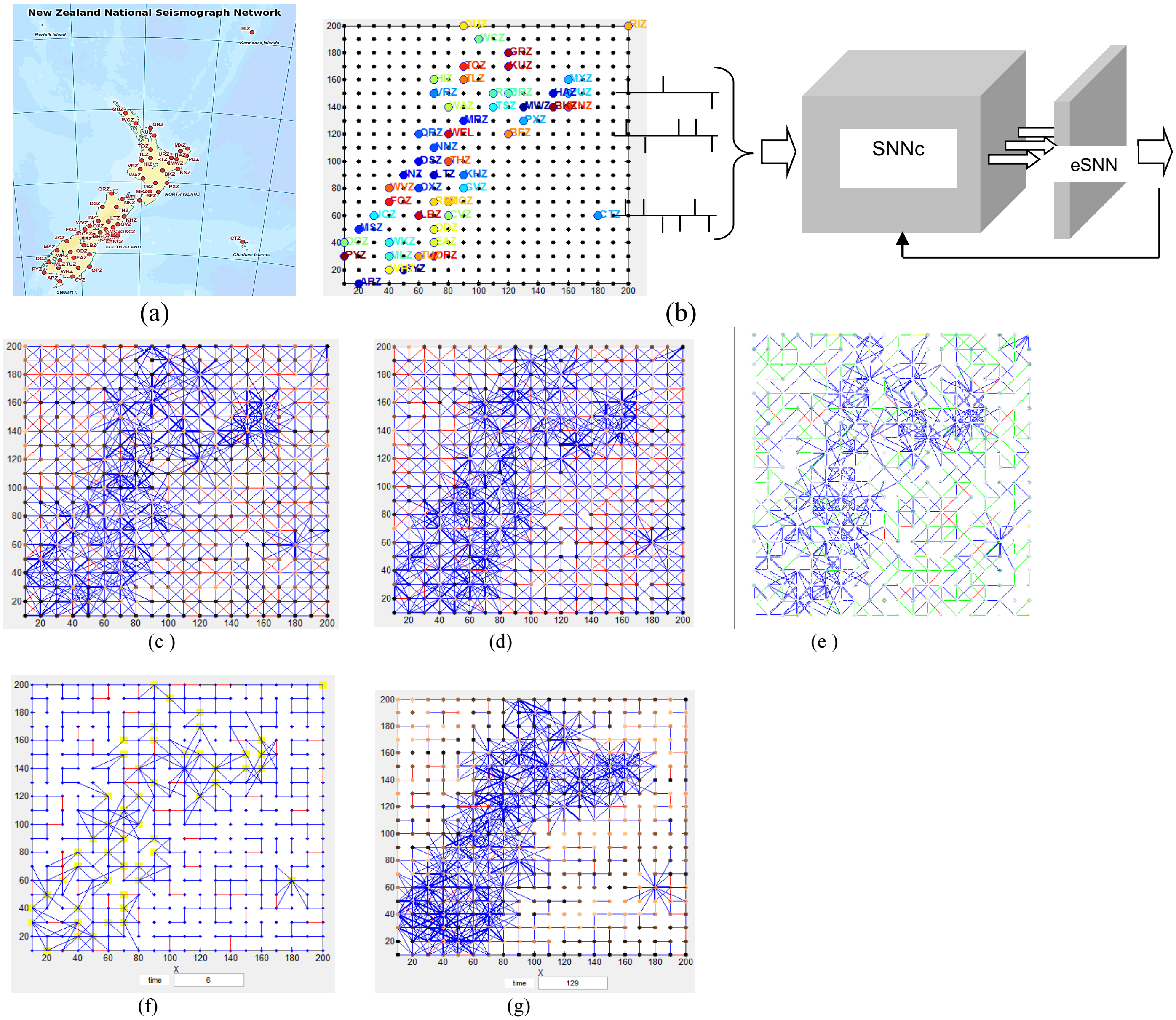

Fig.1 (a) A view of NZ seismograph network of seismic sites; (b) Stream data from 52 seismic sites are entered continuously into a NeuCube model as trains of spikes, the model consisting of a 3D SNNcube trained in an unsupervised mode and an output classifier/regressor implemented as evolving SNN; (c) A 2D view from above of a NeuCube model trained on 12 samples of 52 variables measured for 100 hours before an unnoticeable event in Christchurch (ChCh) is registered 1 hour later; connections represent spatio-temporal relationships between the measured seismic sites; (d) A NeuCube model trained on 12 samples of the same size as in (c), but preceding a severe earthquake in ChCh 1 hour later; (e) The difference between the models from (c) and (d) represents the abnormal spatio-temporal associations between seismic activities in all 52 cites in the last 100 hours, 1 hour before the severe event in ChCh; (f) a spatio temporal map of seismic activities in NZ 95 hours before a severe event in ChCh and (g) seismic activities in NZ 1 hour before the event; these are animated pictures that can be run over time to show the spatio-temporal dynamics of the seismic changes in NZ before the severe event in ChCH (they need to be opened in a browser, also available at: http://www.kedri.aut.ac.nz/neucube/seismic/).