Earthquake Detection and Focal Mechanism Calculation Using Artificial Intelligence

Shane Quimby
GeoTomo
Yanwei Zhao
GeoTomo
Dr. Jie Zhang
GeoTomo

Summary

In this paper we present recent work leveraging the advances in deep learning to propose a novel deep convolutional neural network Focal Mechanism Network (FMNet) for estimating the location, magnitude and source focal mechanisms of earthquakes rapidly, using full waveforms. We outline the method, discuss the results achieved thus far, and summarize some current and future uses for the system.

Article text should be Arial 11pt, left and right justified. 2 pages including a graphic is suggested (not required). Please use the headings that are appropriate for your work, deleting the ones that are not.

Theory / Method / Workflow

Before being used to detect earthquakes (or events from induced seismicity), FMNet must be trained. This can be done in two ways. The traditional way is by using historical data from the area. Unlike most AI methods, it can also be trained with synthetic data. This serves as an advantage in areas without enough historical earthquake data available for training the neural network; especially for those regions with limited recorded seismicity but having the potential for damaging seismic activity.

To generate a synthetic dataset, we discretize the three-dimensional (3D) grid space of the study area. We simulate theoretical waveforms with a variety of focal mechanisms at each spatial grid point. We train the FMNet model with the synthetic or historical dataset and then apply it to calculate the locations and focal mechanisms of subsequent earthquakes. FMNet extracts and learns the essential features of the waveforms from the training dataset, incorporating it into the neural network. This makes re-visiting the database unnecessary. FMNet only stores the neural weights of a few megabytes in memory, which enables it to operate in real-time. During monitoring, FMNet only takes about 200 ms to complete analysis once the data has been received.

The neural network we designed can be described as a fully convolutional network (FCN). FCNs are supervised deep learning networks based on convolutional layers, without being fully connected. This necessitates fewer model parameters, leading to high computing efficiency.

The output of the network is not a single location, but a large number of pixels representing a 3D image, in which the peak value corresponds to the most likely source location in the subsurface. It requires no manual picking.

Results, Observations, Conclusions

The results obtained using the above method have been compared to results obtained by large scale national earthquake detection networks, as well as to smaller regional networks designed to detect induced seismicity. Both sets of comparisons yielded impressive results. Event locations, magnitudes and focal mechanism estimations were all close to accepted calculations.

Novel/Additive Information

The method and the software that utilizes it were initially designed to serve as an early warning system for earthquake detection in China. Currently it is operating with three seismic networks in Sichuan, and each network consists of over 200 seismic stations. It is significantly faster than current widely used alert systems. Due to the efficiency of the FCN described above, location magnitude and focal mechanism solutions can be arrived at in 10-20 seconds, and an alert generated within a couple of minutes. This compares with anywhere from 10-45 minutes for the alerts currently generated by nationally operated detection networks. In addition to its initial purpose, there are several other potential uses.

The first, induced seismicity has already been covered briefly. The ongoing concern with induced seismicity may soon result in compulsory monitoring of oil and gas field. In this case, an automated method like the one described above is almost necessary since the manpower to monitor these fields simultaneously does not currently exist. Long-term reservoir monitoring, which is somewhat of a parallel to induced seismicity monitoring, could also be served by this method.

This type of detection network could also be used to monitor seismic activity and reservoir integrity for carbon capture and storage (CCS) projects. The path to net-zero carbon will need to be composed of many methods, and CCS will undoubtedly be one of these. The network can track the extents of the plume and give feedback on reservoir integrity.

Another potential use for is for geothermal monitoring. As the world strives to increase energy production without increasing carbon emissions, geothermal energy will become more prevalent. Automated detection networks will be needed to ensure that fluid injection does not cause excess seismicity.

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References

Zhang, X. et al. Locating induced earthquakes with a network of seismic stations in Oklahoma via a deep learning method. Sci. Rep. 10, 1–12 (2020).

Kuang, W., Yuan, C. & Zhang, J. Real-time determination of earthquake focal mechanism via deep learning. *Nat Commun* **12,** 1432 (2021). https://doi.org/10.1038/s41467-021-21670-x.

Figure 1. Display showing an earthquake located in China. The left panel shows the seismic traces along with the focal mechanism solution. The right panel shows arrows connecting the stations that were used for calculation to the event location. The bottom right panel shows that it was only 90 seconds from the occurrence of the quake until an alert was sent out.

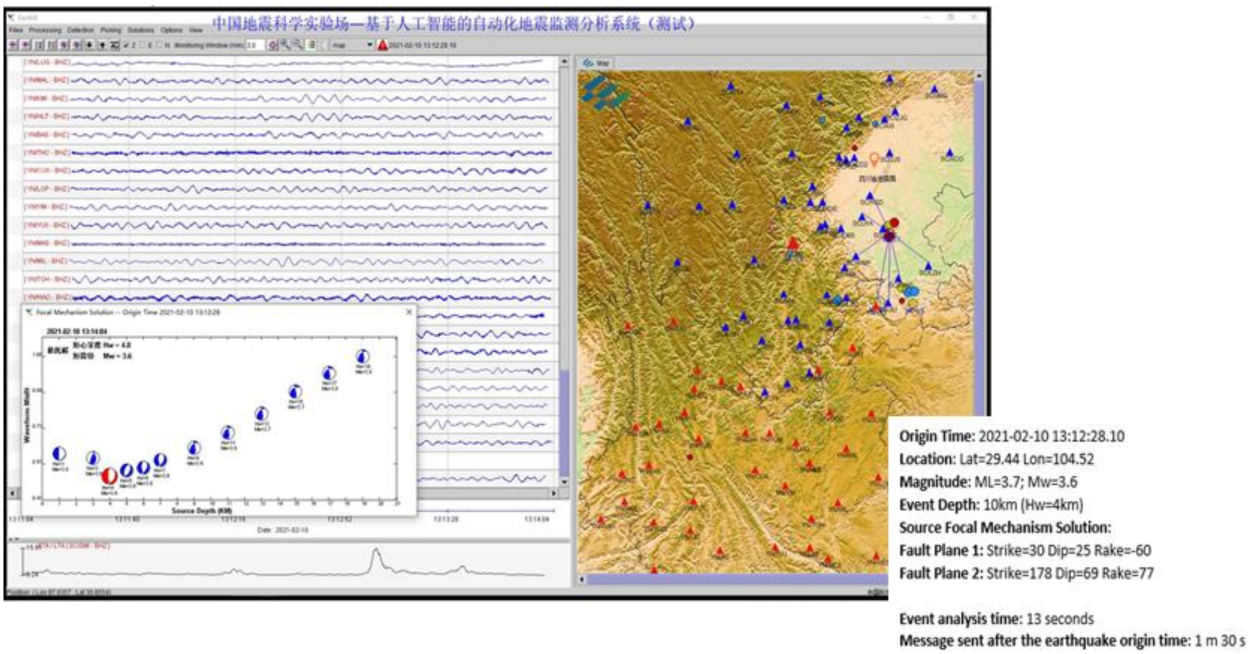

Figure 2. Table showing EarthX results compared to the results compiled by CSES (China Seismo-Electromagnetic Satellite). The two tables compare results from 2 separate networks in China. Our results compare favorably with accepted locations. The results for the smaller, denser network in the bottom table are closer than for the sparser network.

92 stations, more than 1 million sq.km. monitoring area Jan.2020 -- Dec.2020			
Epicenter Deviation (km)	3.0	Origin Time Deviation (sec)	1.2
Depth Deviation (km)	5.0	Magnitude Deviation(ML)	0.21
Locating Time-consuming (sec)	6.4	FMS Time-consuming (sec)	8

178 stations, 0.8 million sq.km. monitoring area Mar.2021 -- May.2021			
Epicenter Deviation (km)	2.0	Origin Time Deviation (sec)	0.8
Depth Deviation (km)	2.5	Magnitude Deviation(ML)	0.13
Locating Time-consuming (sec)	4.2	FMS Time-consuming (sec)	8