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Rapid prediction of earthquake ground shaking intensity using raw waveform data and a convolutional neural network

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Abstract

To produce a rapid prediction of earthquake generated ground motions, on a short timeline after earthquake origin time, seismological community has been developing earthquake early warning systems, which seek to very rapidly (few seconds) detect earthquakes and provide predictions of ground motions at selected target points, for the purpose of providing early warning at those points.

Key words: Earthquake early warning, earthquake ground motions, meural metworks, time series analysis

To produce a rapid prediction of earthquake generated ground motions, on a short timeline after earthquake origin time, seismological community has been developing earthquake early warning systems, which seek to very rapidly (few seconds) detect earthquakes and provide predictions of ground motions at selected target points, for the purpose of providing early warning at those points. Recently, machine learning techniques have been more intensively used in seismology with great success, including applications for earthquake early warning purposes (e.g. [1], [2]). A lot of success in the application of machine learning to seismic waveforms has come from the use of Convolutional Neural Networks (CNNs), especially in earthquake detection. In this study we explore the use of CNNs for rapid prediction of earthquake ground shaking using only the initial N seconds (after the earthquake origin time) of the waveform recordings at a set of stations. We assume that the CNN model will be able to learn, from the patterns of signal and noise accross the stations in the input vector, the characteristics of the earthquake and a kind of locally calibrated GMPE directly from the observed data, which would then be used for predictions of ground shaking.

In a recent study [3], we showed that CNNs applied to network seismic traces can be used for rapid prediction of ground motion at distant stations using only the recordings from stations near the epicenter. The inputs to the CNN model are the multistation (39 stations in the study), 3-component acceleration waveforms of earthquakes recorded during the central Italy sequence of 2016. The dataset consists of records 915 earthquakes with $M \geq 3.0$ (Fig. 1a) and 1037 noise-only examples. All the input waveforms start at earthquake origin time and are 10 seconds long, where 10 s was used as we found it provided the best compromise between the accuracy of the predictions and the timeliness. Targets of the CNN are peak ground acceleration (PGA), peak ground velocity (PGV), spectral acceleration (SA) at 0.3, 1 and 3 s periods on the 39 stations that are used for input. In practice this means that for the stations that are close to the earthquake epicenter the maximum of the ground shaking has already been recorded. However, for more distant stations, for which the maximum ground shaking was not recorded in the 10 s input window, the model will be able to give predictions of the maximum ground shaking expected. If the data are missing for some station we fill the inputs with zeros and use the ShakeMap predictions as IMs on those stations (using the latest configuration for Italy [4]), so the CNN model has approximate targets during the training. The CNN model consits of 3 convolutional layers followed by one fully connected layer of size 128. The filters in the first two convolutional layers analyze single station waveforms, while the filters in the third layer analyze patterns across the 39 stations. We train the network for 12 epochs, using a batch size 5 and mean squared error as the loss function. The data has been split into training (80%) and test (20%) subsets, with the results evaluation done using 5-fold cross-validation technique.

We find that the CNN is capable of accurately predicting IMs at stations far from the epicentre which have not yet recorded the maximum ground shaking by using a 10 s window (that starts at earthquake origin time). The results of the CNN model have been compared to those obtained by the Bindi et al. GMPE [5] (which used final location and magnitude), and they showed that the CNN features similar variance and smaller bias (absolute median of CNN residuals ~ 4 times lower) of the residuals between the observed and predicted values. It should be noted that the between-event correction was not applied on the GMPE results, which would reduce the bias of the GMPE residuals. This suggests that the CNN model learns and applies the between-event correction automatically. The results of the CNN model are similar for the cases in which input waveform at the station exists or not. Including samples of noise-only waveforms in the CNN training showed that the CNN was accurately predicting the IMs corresponding to the noise amplitude recorded at the station. This shows that the technique could be applied in real-time streaming.

The dataset used in the study [3], however, consists of waveforms recorded on a dense network of stations for a large number of spatially concentrated earthquakes (Fig. 1a). To test our algorithm on a more challenging problem, we trained the same CNN model on a smaller-sized dataset in a different area. We chose the area around the VIRGO gravitational waves observatory sited near Pisa, Italy, which could greatly benefit from an EEWS to shut-off the instruments in case of significant earthquakes nearby. The dataset for this area consists of 266 $M \geq 3.0$ earthquakes recorded by 39 stations between 1 January 2013 and 20 November 2017 (Fig. 1b), with input and output data following the structure already described above for study [3]. We found that the results of the CNN model worse compared to the results presented in the previous study [3], which was expected due to the smaller training dataset size. To overcome the problems associated with training the CNN model on a smaller-sized dataset we adopted the transfer learning methodologies: using a model pre-trained on a different dataset as the initial model for training the CNN model. We explored two approaches: 1) using a pre-trained model trained on the dataset from [3] 2) using a pre-trained model trained for single-station magnitude determination on 1 milion waveforms. The results of the CNN model, when transfer learning was used, show improvement in terms of outliers, median and variability of the residuals between predicted and true PGM values. The possible use of the CNN model for EEW is demonstrated by the warning times on the station PII (located 10 km from the VIRGO observatory) that would be received if the model was active during the analyzed earthquakes.

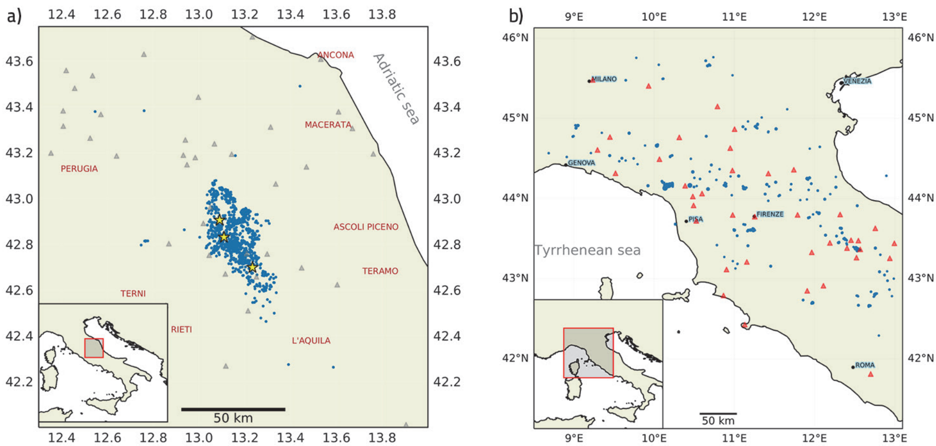

Figure 1. Maps of the application areas: a) Central Italy area. Earthquakes illustrated as blue points, stations as gray triangles. b) Pisa-centered area. Earthquakes illustrated as blue points, stations as red triangles

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