Combining CNN and RNN in Seismic Phase Picking

Poster #194

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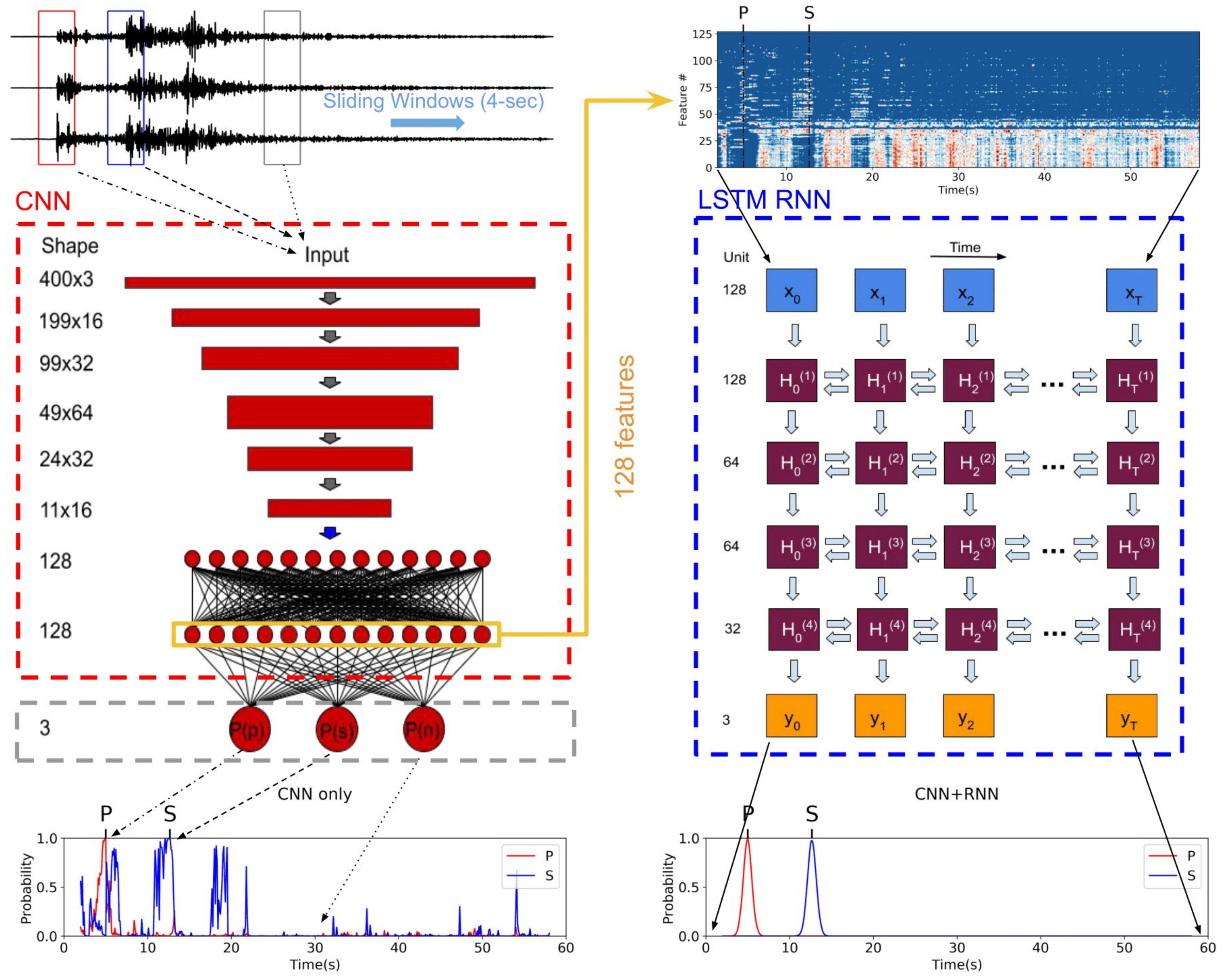
Introduction

The recent expansion of seismic data and computing resources enables flourishing applications of deep learning in seismology. Many studies aim at automatically picking P and S arrivals, especially those buried in noises. Dozens of deep-learning-based models prove to be efficient in detecting phases of local events (<300km). Most of them take seismograms/spectrograms as input data and output the probability of P/S/background phases.

Previous studies treat inputs as images and focus on the Convolutional Neural Network (CNN). CNNs employ filters within convolutional layers to extract features from inputs, and are often used in computer vision to recognize objects and patterns in images. Recent studies notice that input seismograms/spectrograms are sequential data, more like audio. Recurrent Neural Networks (RNN) are designed to interpret temporal or sequential information, which is widely used in speech recognition. However, RNNs cannot be stacked into very deep models and training an RNN is a very difficult task. We can solve this problem by extracting features from a pre-trained CNN model and then training a RNN on top of it. This strategy is called transfer learning, which has the benefit of decreasing the training time and producing smaller generalization errors.

Methods

Figure 1



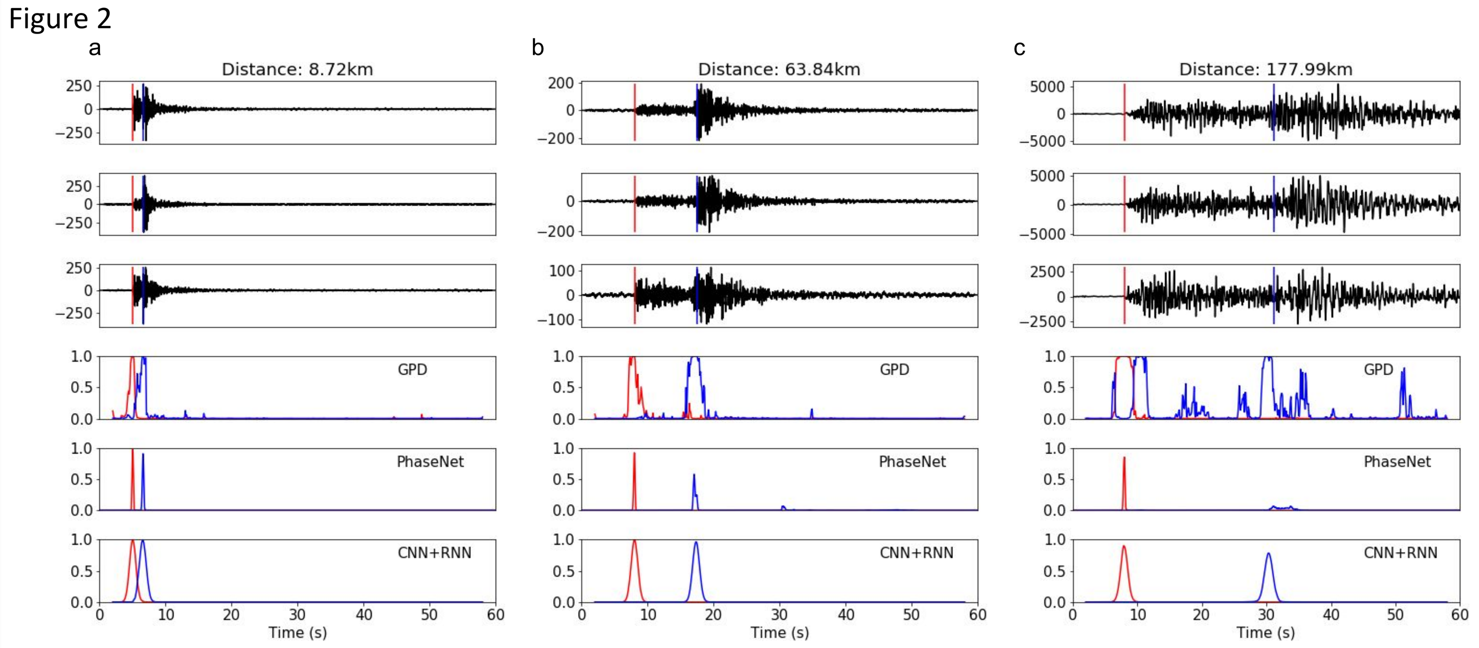
Our model takes advantage of both CNN and RNN. The CNN model extracts features related to P and S phases from raw seismograms, while the RNN model recognizes signals from the time-related context. We first train a CNN model composed of five convolutional layers and two fully connected layers to classify a 4-sec small window segment as P/S/background noise. Instead of outputting the final layer (3 features or probabilities), we output the feature map of the second last layer (128 features). We then train a bidirectional Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) model on top of the CNN classifier. The RNN model has 4 hidden bidirectional LSTM layers with tanh activation function. The input of RNN is a sequence of 128 features extracted by the last second layer of CNN, and the output is the sequence of the probability of P/S/Background. The CNN model parameters are fixed when we training the RNN model.

Data

To train the CNN network, we adopt the labeled seismic data recorded by the Southern California Seismic Network (SCSN, Ross et al., 2018). The database is composed of 4.5 million 4-sec three-component waveforms of P, S and noise earthquakes (1.5 million per category). We then train the RNN model, by adopting the STanford Earthquake Dataset (STEAD, Mousavi et al., 2019) with seismograms recorded by 2,613 globally distributed seismic stations. It contains 1 million 60-sec three-component waveforms labeled with P/S arrival time. We split the seismograms (~550,000) into a training set and a testing set (~50,000), and the two sets share no common stations. This procedure is designed to test the generalization ability of our model to different stations/networks/regions.

Results

Figure 2



Compared to the model trained directly with CNN (PhaseNet, Zhu et al., 2019; GPD, Ross et al., 2018), our CNN+RNN hybrid model achieves better performance. Figure 2 shows three examples in the testing set with different hypocentral distances. All models perform well in the near distance (Figure 2a, Figure 4g-i). However, at further distances (Figure 2b-c, Figure 4g-i), the GPD model tends to produces more false detections and the PhaseNet mode tends to miss S phases. To measure the false and missing detection rate, the pickers with residuals (< 0.5 s) are counted as true positive picks.

Figure 3

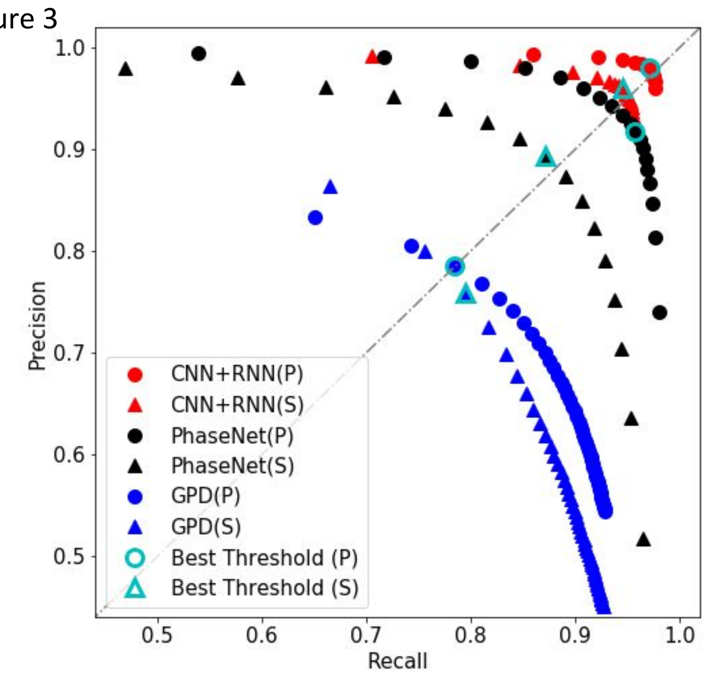
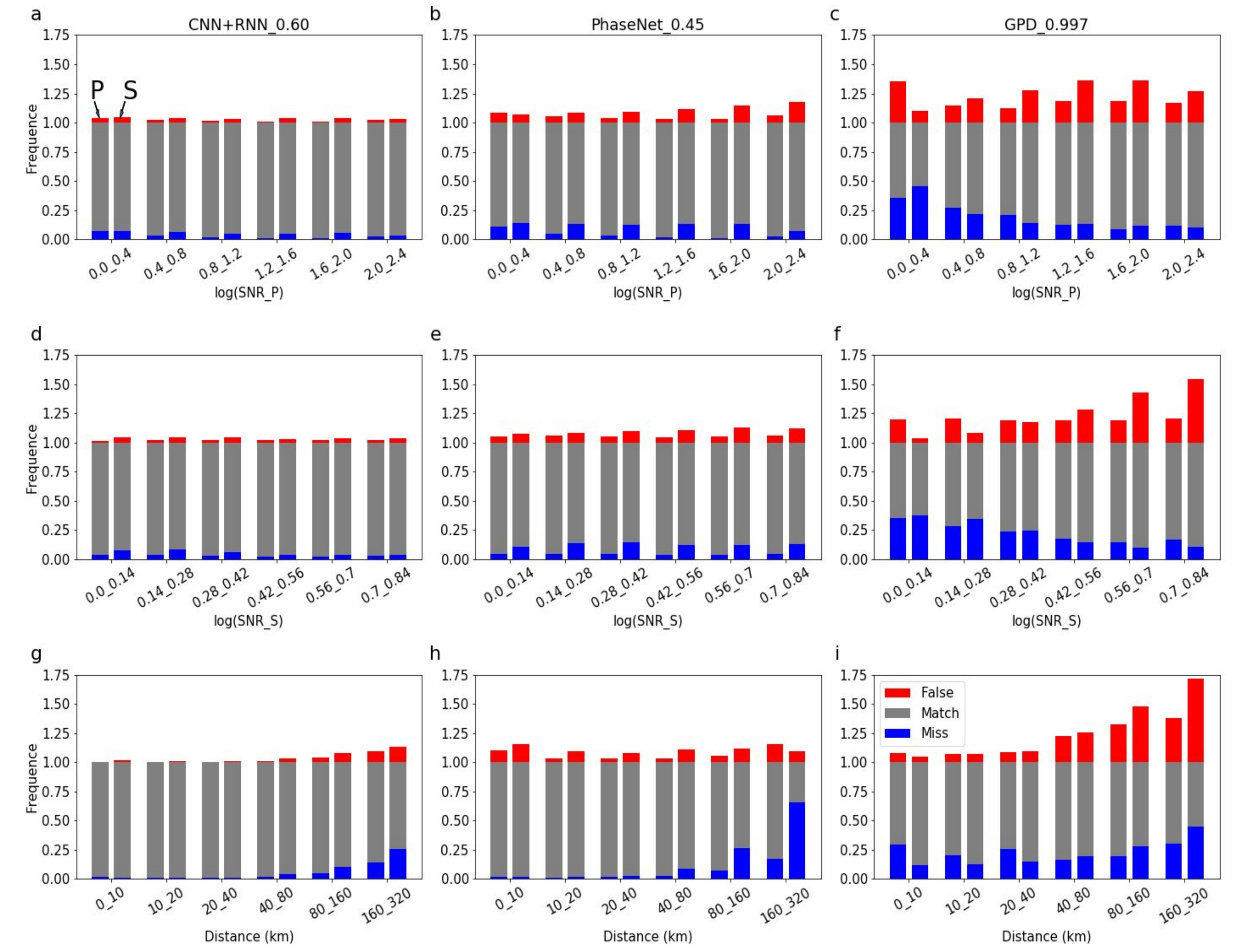


Figure 3 shows the precision and recall trade-off curve of PhaseNet (blcak), GPD (blue), and our CNN+RNN hybrid (red) model on the testing set. The hybrid model outperforms GPD and PhaseNet in term of the area under the curve. We then select the best threshold (cyan) of each model (CNN+RNN: 0.60, PhaseNet: 0.45, GPD: 0.997) based on the maximum F1 score (average of P and S), which is then used in the analysis of Figure 4 and 5. The F1 score is the weighted average of precision and recall.

Figure 4



The data quality is essential to the model performance, therefore we measure the quality of testing set based on three different index: signal-to-noise ratio (SNR) of P wave, SNR of S wave and hypocentral distance. For each index, we group the testing set into 6 bins and normalized the bin size. Figure 4 shows the performance of CNN+RNN hybrid model (a,d,g), PhaseNet (b,e,h), GPD (c,f,i) changing with three index. At each tick of the horizontal-axis, the left bin represents the P wave while the right bin represents the S wave. Each bin is composed of 3 portions: matched (gray), missed (blue) and false (red) detections. The number of ground truth arrivals equals the summation of matched and missed phases, which is normalized to 1. We can find that the hybrid model is more robust to low SNR of P and S than two other models. In additional, the miss and false detection rate of all models increase rapidly with the distance, especially larger than 40 km.

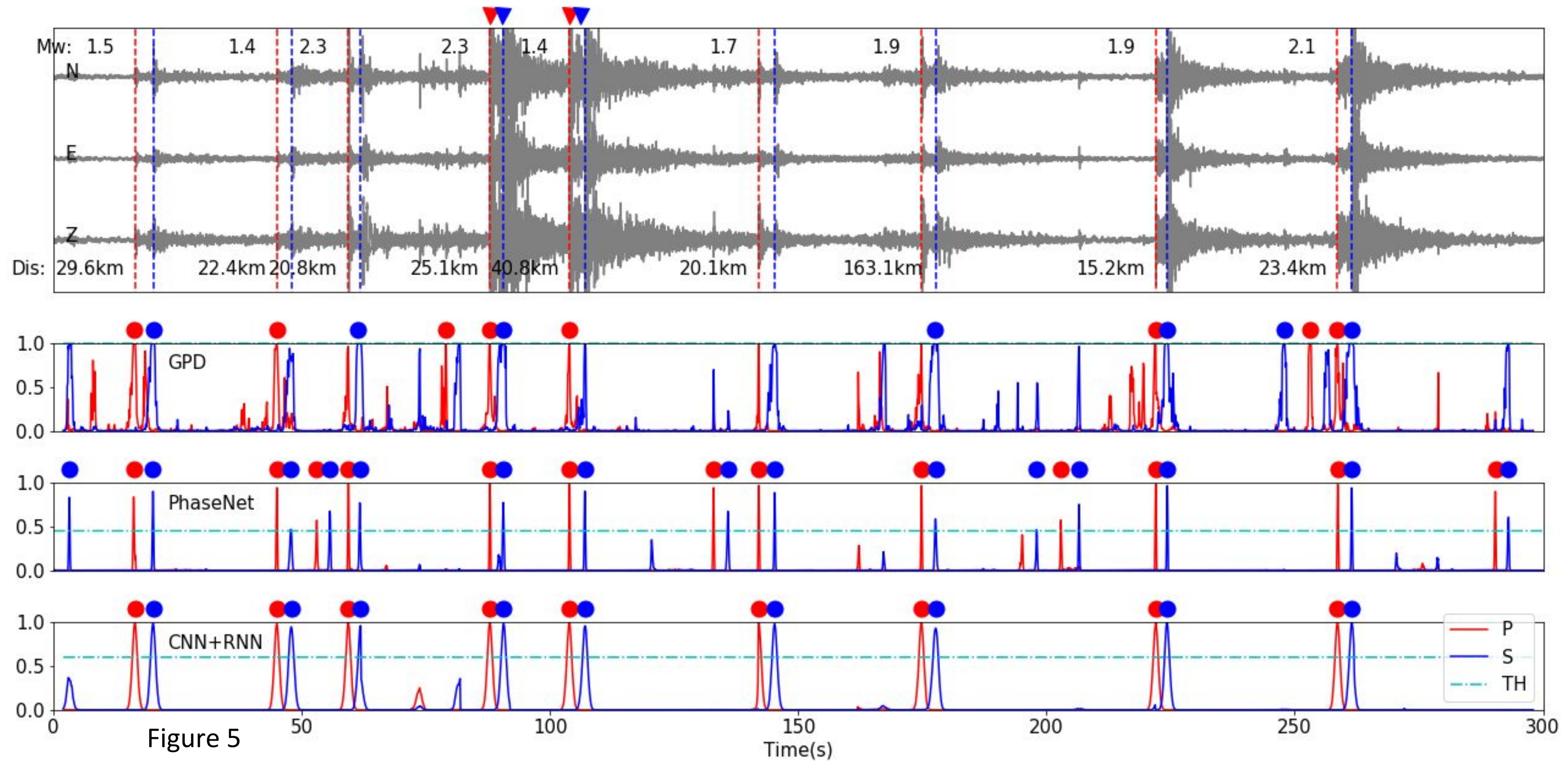


Figure 5

We test the generalization ability of three models with 5-min continuous waveforms from a Hi-net Station (N.HTAH, start from 2011-04-12 17:33:20 JST). The JMA catalog recorded 9 events but only manually picked phases of 2 events (triangles). We estimate the theoretical P (red dash line) and S (blue) arrival time based on the JMA catalog and IASP91 velocity model. If we take JMA catalog as ground truth, CNN+RNN hybrid model is the most robust with no false or missing detections, we can not rule out that the additional detections by PhaseNet or GPD are smaller micro-seismicities.

Summary

In the seismic phase picking task, we build a hybrid model by combining CNN with LSTM RNN through the transfer learning. Compared with models trained directly from CNNs (PhaseNet and GPD), our hybrid model has higher accuracy and precision in the testing set. In addition, the hybrid model is more robust against low SNR of waveforms and far hypocentral distances, which indicates better generalization ability. Finally, we test the performance of the model on the 5-min continuous waveforms of a Hi-net station. Our model detects all P and S phases recorded in the JMA catalog without any false detections. The successful application on continuous waveforms indicates that our CNN+RNN hybrid model can potentially improve automatic phase picking in monitoring large seismic networks.

Reference

Mousavi, S. M., Sheng, Y., Zhu, W., & Beroza, G. C. (2019). STanford EArthquake Dataset (STEAD): A Global Data Set of Seismic Signals for AI. *IEEE Access*, *7*, 179464-179476.
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