684578: A Machine-Learning-Based P-Wave Detecter and Picker for Acoustic Emission Events in Laboratory Experiments

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Abstract

Deformation experiments are conducted under controlled pressure and temperature in laboratory and acoustic emission (AE) events are monitored by transducers during the experiments. Accurate first P-wave arrival times are needed for locating the events. There have been several machine-learning-based methods to pick P-wave arrivals in waveform records of individual stations. Here we developed a new method to detect AE events and to pick their P-wave arrivals at multiple transducers simultaneously. We treated waveforms recorded by different transducers as a 2D image and applied a convolutional neural network (CNN) to classify the image to detect AE events. We then applied a fully convolutional network (FCN) to do image recognition to pick P-wave arrival times. We tested the method using data from a transformational faulting experiment on Mg2GeO4. P-wave arrival times of 550 AE events were manually picked at 6 transducers. We chose 50 events and randomly cut each of their waveform records into 100 segments to train our model. The trained model was then applied to the waveform records of the rest 500 events. 488 events were detected by CNN. About 99% P-wave arrival times were picked by FCN with an error less than 0.5 micro seconds compared with the manually picked times.

Introduction

Nanoseismological studies apply seismological techniques to monitor and analyze AE events in laboratory experiments. Compared to direct observation, more detailed quantitative information can be provided including events' distributions and source parameters. One of fundamental problems is to detect and pick the first P-wave arrival times. Accurate P-wave arrival times can be used to locate AE events, determine P-wave amplitudes and waveform which is essential for further study. Performance of traditional autopick methods including Short Time Average over Long Time Average (STA/LTA) is always influenced by events' magnitudes and strength of noise and instrument response.

We develop an efficient and reliable autopick method using neural-network technique.

Neural Network

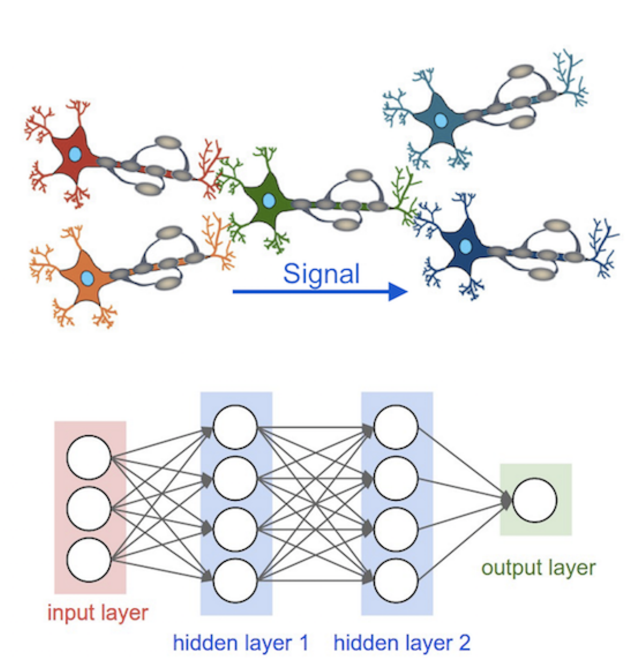


Figure 1: An artificial neural network (bottom) simulate human neural network (top) to make prediction.

1. **Multiple layers** arranged sequentially. **Many parameters** inside each layer.
2. **Train neural network** with labelled data to optimize parameters.
3. Trained network can **make prediction** with an input.

Method

Limitations of previous neural-network based autopick methods:

1. Most waveform data donât contain event information.
2. Using 1D-time-series data ignore the correlation of waveforms of an event recorded by different stations.

How we improved:

1. pick: classification (detect) + recognition (pick)
2. 1D time-series data at different channels: 2D waveform image.

Detecter: CNN

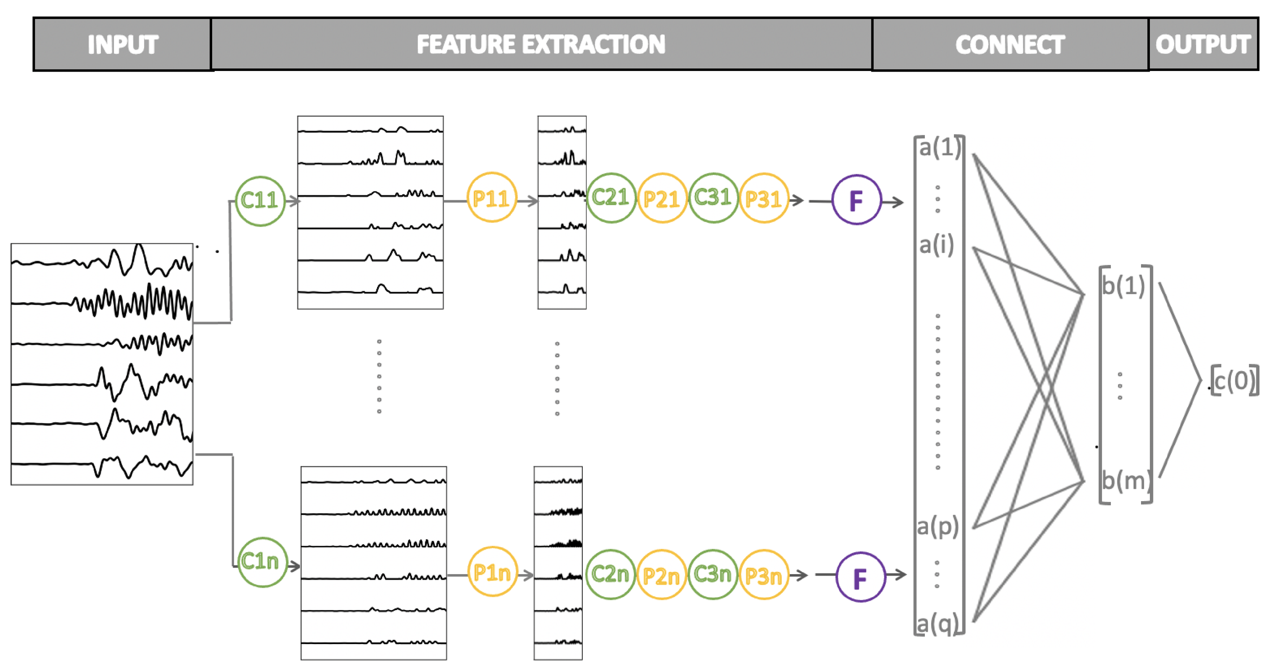


Figure 2: Architecture of CNN. C: Convolution layer. P: Pooling layer. F: Flatten layer. It takes a waveform image as input and output a probability of an event in the waveform image.

Picker: FCN

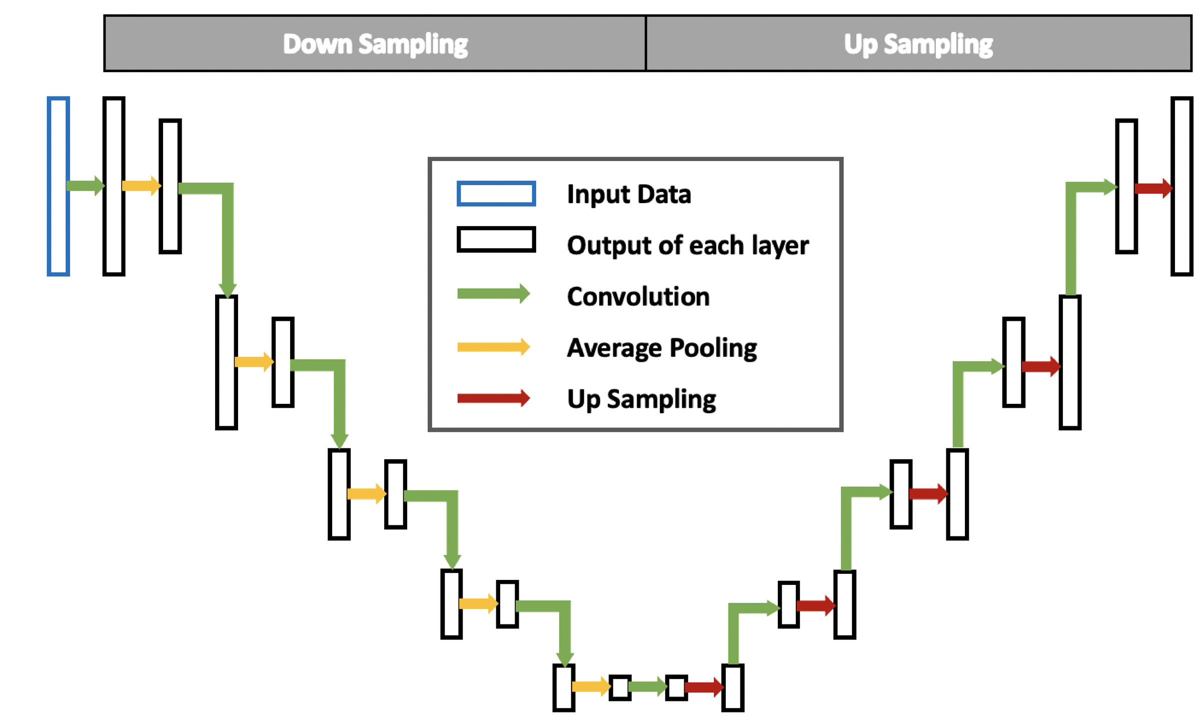


Figure 3: Architecture of FCN.It takes a waveform image as input and output a corresponding-size output. Each element is the probability of P-wave arrival time at each point.

Procedure

1. Waveform data at different channels are aligned and cut into waveform-segment images.
2. Waveform-segment image is passed to CNN to detect AE events.
3. If the output of CNN over a threshold, the image will be passed to FCN to pick P-wave arrival times.

Data and Result

We applied our method to autopick first P-wave arrival times in olivine experiment data [Wang et al., 2017]. 550 events at 6 channels have been manually picked with a sample rate of 0.02 μs. A time window with a length of 10.24 μs is used to cut the waveform.

50 events are randomly chosen and used to train data. During the training, a binary-corssentropy function is used as a loss function for CNN and a mean-square-error function is for FCN.

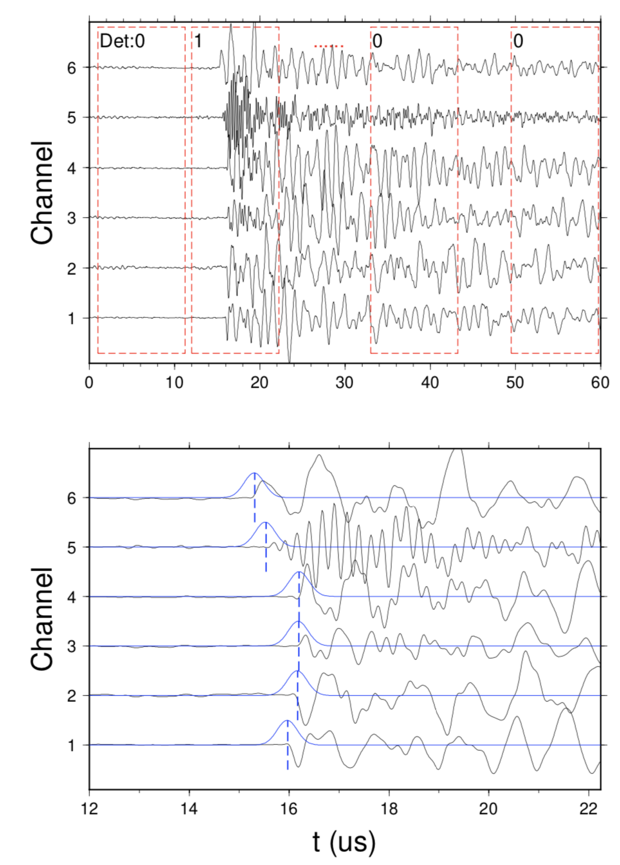


Figure 4: An example of an event chosen to train the network. Waveform data of AE events are randomly cut into 100 segments (red dashed squares). For the CNN detector (top), labels are 1 or 0 depending on whether images contain the first P-wave arrivals. For the FCN picker (bottom), labels are Gaussian distributions of P-wave probability with σ=0.2 μs based on manually picked arrival times (blue dashed line).

The rest 500 events are used to autopick P-wave arrival time.

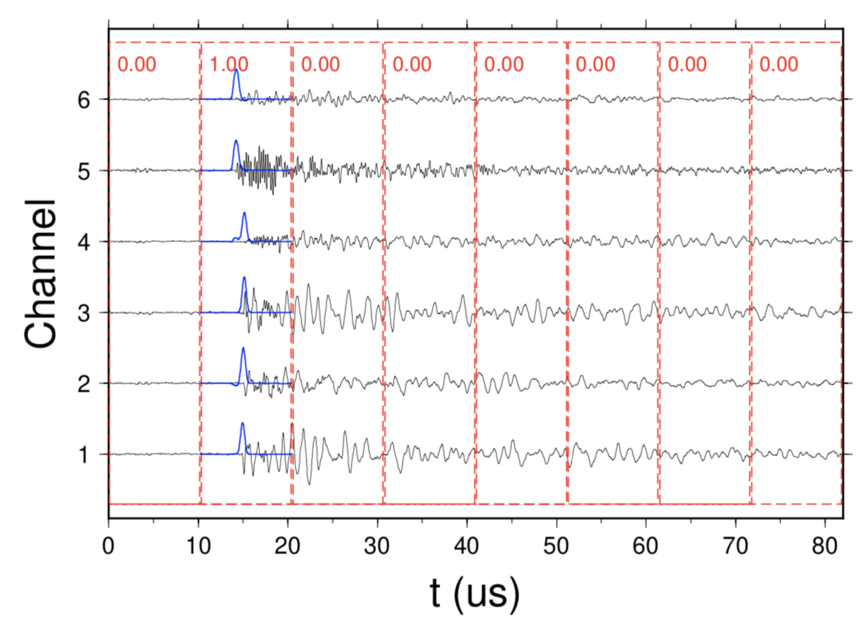


Figure 5: An example of a test event 227 used to predict P-wave arrival time. Waveform data are cut into 8 waveform images in chronological order (red dashed square). If the output of CNN over 0.6 (red number), the waveform image will be passed to FCN. The maximum of output (blue line) in each row is the corresponding P-wave arrival times.

487 events were detected and picked. 13 events were missed. 1 fake event was generated. In 487 events, analysis of autopicked arrival times at 6 channels are shown in Table 1.

Channel	01	02	03	04	05	06
Accuracy (< 0.5 μs)	99.6%	99.6%	97.9%	99.2%	97.5%	98.77%
Mean (μs)	-0.02	-0.03	-0.08	-0.02	-0.00	-0.04
Standard deviation (μs)	0.28	0.28	0.32	0.30	0.32	0.30

Table 1: Statistic analysis of autopick error at Channel 1-6.

Discussion

Compare with STA/LTA

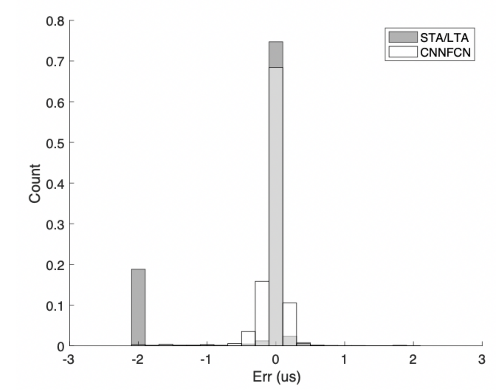
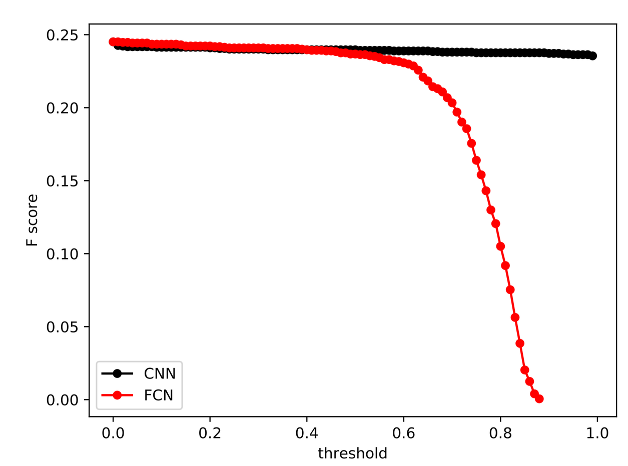


Figure 6: A histogram of error of autopick results with STA/LTA and our method.

The performance of STA/LTA highly influenced by the noise. 20% events have error bigger than 2 μs.

CNN to classify waveform images



CNN have a robust performance with different thresholds. We introduce F-score to evaluate the ability of detection. F-score of CNN and FCN on detection as a function of threshold is shown in left. The performance of CNN has little influence of the threshold compared with CNN.

Using 2D waveform images instead of 1D time series

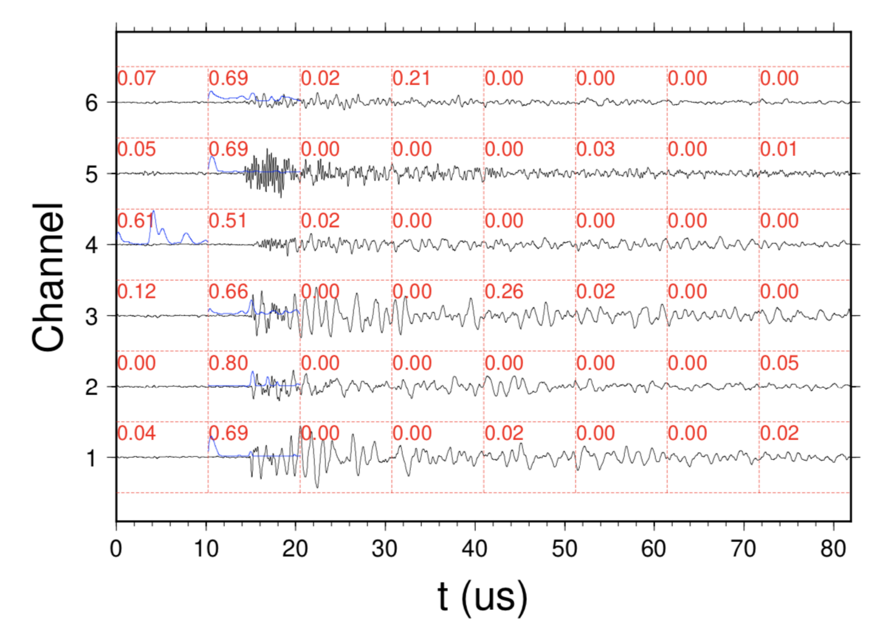


Figure 7: An example of test event 227 using 1D neural network to autopick P-wave arrival times. Each 1D segment (red dashed square) is as the input. Red number: CNN output. Blue line: FCN output when CNN output over 0.6.Because of the different quality of data at each channel, the performance is not stable at different channels.

Conclusions

1. We develop an autopick methods with machine-learning technique and apply it to pick P-wave arrival times of AE events in laboratory experiments.
2. The method hold good promise on variant thresholds and different qualities of data.

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