Automatic first arrival picking for borehole seismic data using a pixel-level network

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Summary

First arrival picking is the basis of the following seismic processing and imaging. The most widely used method, manual picking, is labor intensive, time-consuming as the seismic data volumes grows sharply. Robust and automatic picking methods need to be developed to meet the challenges. We propose a novel method to automatically pick the first breaks using an improved 2D pixel-wise convolutional network. Events picking is transferred into a problem of binary image segmentation through respectively tagging signal before and after first arrivals as one and zero. Field examples with borehole seismic data are used to demonstrate the effectiveness in reduce labor and superiority over traditional automatic picking methods.

Introduction

First arrival picking, or events picking, is the basis of the following efforts in seismic processing and imaging. Manual picking, as the most widely used method, can be labor intensive and time-consuming. This process usually takes at least twenty percent of the total data processing time. In addition, its accuracy highly depends on the visual perception and experience of interpreters. As the seismic exploration moves toward high-density acquisition, a large number of automatic or semiautomatic methods are developed to keep up with the increasing data volume. One of the most common approaches is based on energy analysis. For example, the short-term average over long-term average (STA/LTA) method declares an event when the STA/LTA value first exceed a user-provided threshold (Allen, 1978). However, STA/LTA is sensitive to real noise and may miss weak events even with an adaptive threshold (Baer and Kradolder, 1987). Another class of methods use waveform similarity estimation to identify events that are similar to a mater event. Song et. al (2010) predefined master events and use cross-correlation to pick events with high similarities between master events and time series. Although template matching is capable of detecting events with low signal to noise ratio (SNR), it is easy to lead to biased picking because it only detects the events that are highly similar to the master events. Furthermore, master events are always required in this process but not always available. Other automatic picking methods include higher-order-statistics (Saragiotis et al., 1999), multi-window algorithm (Chen et al., 2005), transformed spectrum approach (Song et al., 2010), and adaptive filtering (Li et al., 2017). Nevertheless, almost all existing tools require human intervention and only work well in certain conditions. Human labors can hardly be replaced, especially when the subsurface structure is complex. More robust and automatic first-break picking methods need to be developed to meet the challenges.

Machine learning has become a popular technique to deal with complex problems in various fields thanks to its ability to analyze a large amount of data with many variables while avoiding the human biases. In recent years, many machine learning-based events picking methods have been proposed. Various machine learning methods like artificial neural network (Maity et al., 2014), support vector machine (Qu et al., 2018), fuzzy clustering (Chen et al., 2017) have been used to automatically determine seismic signal arrival times. However, most of these algorithms only use 1D features (time series) for training. For regularly spaced receiver arrays, the moveout of first breaks convey additional information that may be helpful to improve picking accuracy. Convolutional neural network (CNN, LeCun et al., 1989) is one of the most popular deep learning algorithms and has also been used in seismic waveforms classification (Yuan et al., 2018). Although CNN considers 2D information of input data to improve the accuracy of events picking, it is compute-intensive and may waste certain information in training data. Firstly, it needs to define a window around the target pixel and then slide the window to cover every pixel in a 2D picture because only the centroid pixel in the window can be classified accurately. Image segmentation assigns a label to every pixel in an image and is effective to detect boundaries or classify input pictures in pixel level through using end-to-end networks. Many networks have been proposed, such as fully connected neural work (FCN, Long et al., 2015), U-net (Ronneberger et al., 2015), SegNet (Badrinarayanan et al., 2015), DeconvNet (Noh et al., 2015). Wu et al. (2019) applied SegNet in first arrival picking of microseismic events and obtain superior performance over STA/LTA. Difference between seismic data and general images are worthwhile to be considered when picking first breaks or events using image segmentation. Pixels in seismic data usually can be classified into two or three classes but images processing need to handle complex patterns.

In this paper, we propose an automatically first arrival picking method based on an improved U-net, which can reduce the human labor in seismic data processing. Firstly, we give a brief introduction to U-net and improve the

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networks based on features of seismic data. Then, we propose an integral workflow from data preparation to prediction. Finally, we apply our workflow to borehole seismic data from Xinjiang oilfield to demonstrate its effectiveness in reduce human labor and superiority over STA/LTA.

U-net architecture

U-net is a deep neural network approach modified from FCN to deal with pixel-level image segmentation. It seeks to localize properties in an image and has been widely used in biomedical image processing. We transfer the first arrival picking into a problem of binary image segmentation through tagging the points before first arrivals as zero and after as one. First arrivals are considered as the` binary between noise and useful signal. The mapping to our problem is to localize the properties our time series into two classes: noise and signal. The original U-net architecture (Ronneberger et al., 2015) is too complicated for our problem of first arrival picking. Difference between seismic data and general images are worthwhile to be considered. We reduce the convolutional layers, max pooling layers, and feature maps at each layer to save memory and computation. To keep same size of input and output images, the padding style of convolutional layers is setting to same, which also avoid the crop step when concatenate two feature maps.

The finally network that we use for first break picking is shown in Figure 1, which is simplified but still preserve good performance in first break picking. As the original U-net, our architecture is an encoder-decoder network that contains a contracting path(left) and an expansive path(right). The input seismic data go through three down-sampling stages and three up-sampling stages. For each stage, we apply one 3×3 convolutional layer followed by a rectified linear unit (ReLu) activation and a 2×2 max polling operation for down-sampling. The down-sampling step is designed to extract and shrink the useful features from raw input data to a neuron. In the right expansion path, every step contains an 2×2 up-sampling operation that expands and converts the feature maps into probability distributions of noise and signal for each pixel. A skip connection at each layer concatenates the left output to the right layer without going through the deeper layer to improve convergence during training (Ronneberger et al., 2015). The final convolutional layer uses a 1×1 kernel with sigmoid activation to map each 8-component feature vector to a probability value for first break prediction. This simplified U-net architecture totally contains 8 convolutional layers.

Input data preparation

As shown in Figure 1, we extract a set of sub images from the raw seismic data as the input for training network, and obtain the final first arrival time by reassigning the outputs of all sub images. We test the workflow using borehole seismic data from Xinjiang oilfield. The main object of the project is to estimate near surface attenuation with strong absorption that is highly rely on the accuracy of first arrival time. We do not use synthetic datasets to train a model because field data is more complicated and the field dataset has more abundant waveforms. The borehole seismic project provides more than hundreds of common receiver profiles and first arrival times have been manually picked by a contractor, which makes the data ideal for training a neural network.

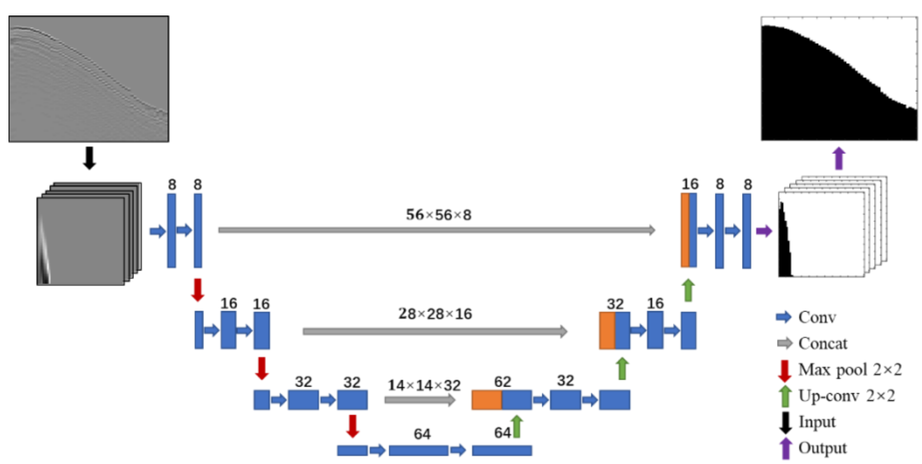

Figure 1: The end-to-end convolutional neural network (U-net) for first arrival picking

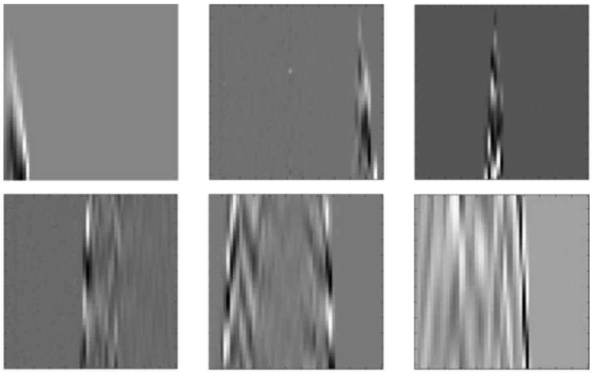

Figure 2: Randomly selected seismic images

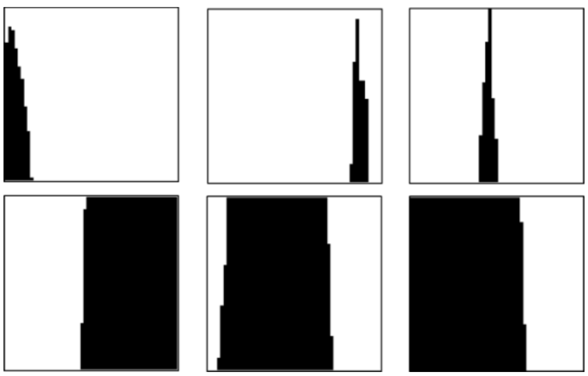

Figure 3: Training labels of input images

Considering the amplitude values of seismic traces can be significantly different from each other, the workflow begins by converting the borehole data after trace balancing into grayscale images with values in the range from 0 to 255. Then we label the seismic data according to the manually picked first arrivals. The points before and after first arrivals are labeled with 0 and 1, respectively. We next extract sub images from raw seismic data with size 56×56, and part of representative input training gray images and corresponding labels are shown in Figure 2 and Figure 3. Creating representative training samples (including seismic images and labels) and keeping high diversity of input dataset are crucial to successfully train the network and prevent the network from learning irrelated patterns. Authors would suggest choose a larger size if the data has more trace and the computer memory is allowed. It needs to be mentioned that totally noisy images (all zero) and signal images (all one) are also input for training.

Training and validation

We train the network using 256 pairs of gray sub images with 20 epochs and the learning rate is set to 0.0001. The validation dataset contains another 100 pairs of such images and labels, which is not included in training dataset. During the training process, the network randomly chooses 30% of the validation dataset at each iteration epoch. Different validation dataset at each epoch can help to provide unbiased evaluation. Figure 4 and Figure 5 show the training and validation accuracy increase to 96% and loss decrease to 0.02 with updating epochs.

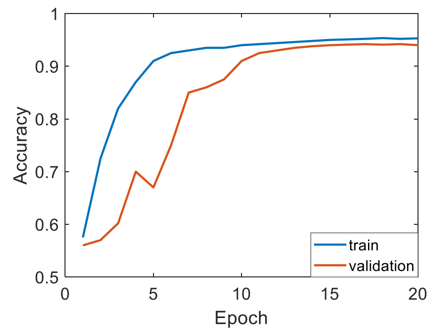

Figure 4: The accuracy of training and validation

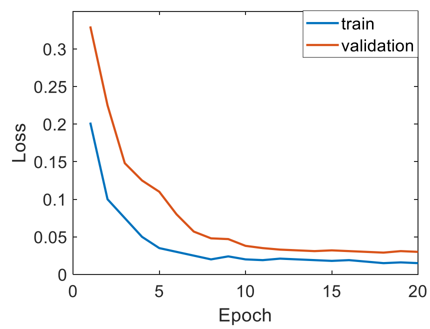

Figure 5: The loss of training and validation

First arrival prediction by U-net

To demonstrate the effectiveness and superiority of our method, we compare U-net with traditional STA/LTA method. 32 pre-stack gathers are used during training the model and we show the prediction of four gathers in Figure 6. Blue dots in Figure 6 are the manually interpreted first arrivals that help to validate our prediction outputs (red dots) as the ground truth. Our method matches well with the ground truth but STA/LTA (yellow circle) failed to pick the first arrivals especially when waveforms become more complicated or amplitude values change abruptly. We further show the distribution of absolute difference between the ground truth with STA/LTA and U-net predicted arrival times for all pre-stack gathers in Figure 7. More than 30 points with extremely big difference ([500-1200ms]) using STA/LTA are not shown to give an obvious comparison with U-net in the similar range. The STA/LTA errors mainly distribute at the range of [-5ms 5ms] while U-net mainly on

[-1ms 1ms]. Our method is more robust for first arrival picking and it does not need to repeatly adjust the parameters for each seismic trace like STA/LTA.

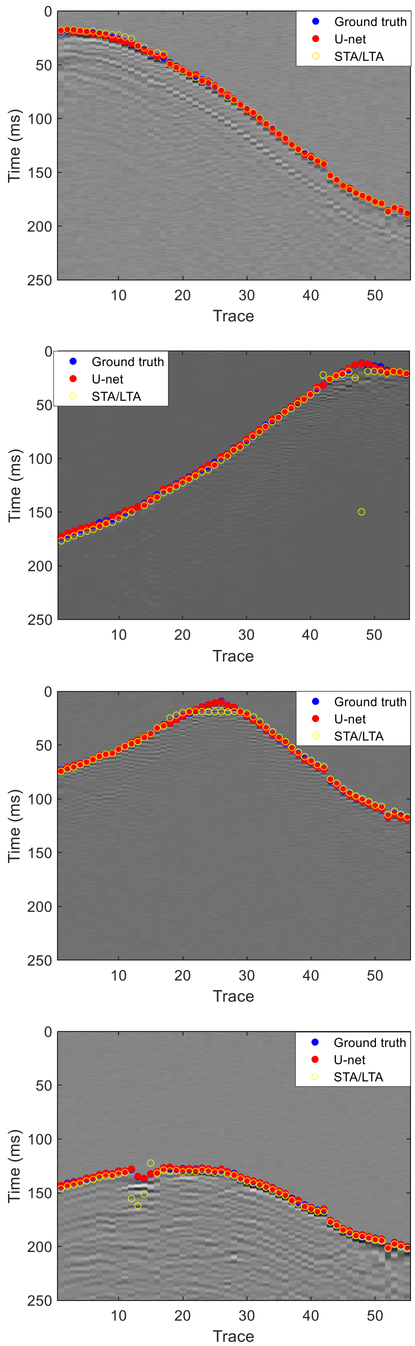

Figure 6: Comparison of U-net and STA/LTA in first arrivals picking for the borehole seismic data.

The training of network is running under GPU GTX 1080 with 12 GB memory. The training process cost one hour and the prediction only need a few seconds That really reduce the human labor in manually picking.

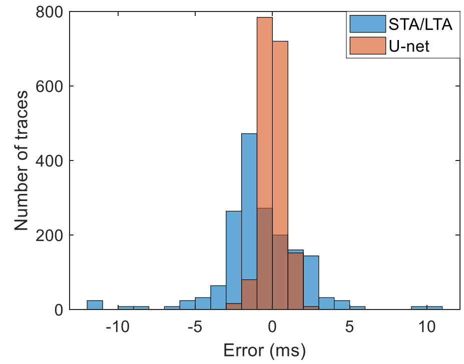

Figure 7: Distribution of difference between ground truth and predicted arrival times (Blue: STA/LTA. Red: U-net)

Conclusions

We propose a novel method to automatically pick the first breaks using an improved 2D pixel-wise convolutional network. Events picking is transferred into a problem of binary image segmentation. The first step is data preparation that balance the amplitude values of each trace and convert seismic data into grayscale images. Secondly, we tag points before and after manual picked first arrivals as one and zero, respectively. Then extracting sub images to form the input data for training. A simplified U-net architecture is built to make it more available for our problem. The final step is to predict the first arrival times from the probability map. Field examples with borehole seismic data show the effectiveness in reduce labor and superiority over traditional automatic picking methods. In the field examples, we use a small size sub images as the input data due to limit seismic traces. For most seismic data like micro-seismic data, smaller trace number easily cause the problem of overfitting. Thus, we suggest choosing 1D network and input data when deal with seismic data with bad horizontal continue features.

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