Fully convolutional network for P-wave arrival detection and time picking using strong-motion data in China

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Abstract

Over the past ten years, the amount of available strong-motion data in China mainland has increased significantly, prompting the need of automatic processing to extract the vast amount of information from such data sets. Meanwhile, the need for seismic analysis and earthquake disaster estimation during quaking demands even more reliable P-wave arrival detection and accurate P-wave arrival time picking. Here, we present a fully convolutional network (FCN) for P-wave arrival detection and time picking onsets for China strong-motion Network. The FCN uses three-component seismic acceleration waveforms as input and generates probability distributions of P-wave arrival time as output. The FCN is trained and tested on the dataset (1708 events) selected from China Earthquake Network Center Catalog (CENC, 2017). The trained network is tested against the short-term average/long-term average united Akaike Information Criterion (STA/LTA+AIC) method, the FCN has an advantage over the STA/LTA method, achieves 99.3% probability in P-wave arrival detection and 98.3% probability in P-wave arrival time picking within the residual error of 0.1s.

Key words: Fully Convolutional Network, P-wave arrival time picking, Strong Motion Records in China

1. Introduction

Accurate and rapid arrival time of seismic p phases are the essential factors in real-time seismology, especially the applications on estimating earthquake parameters rapidly and accurately on mitigating earthquake disaster during and after quaking. Meanwhile, continuous developments in data acquisition and storage have resulted in vast, unprecedented increases in the volume of available seismic data. For large-scale datasets and the need for rapidly picking the arrival time of p phase on mitigating earthquake disaster, the traditionally manual picking methods are facing enormous challenges. In addition, the accuracy of manual picking incorporates the subjectivity of different analysts. Further development of reliable automated picking methods is therefore essential to assist seismologists in their efforts to process large-scale datasets.[25]

Decades of research on reliable automatic phase picker have posed numerous methods on onsets, including: methods based on amplitude, standard deviation or energy; statistical methods and shallow neural networks[29]. The most commonly used method for automatic phase picker is still the short-term average/long-term average (STA/LTA) approach, which tracks the ratio of energy in short-term window/a long-term window and determines phase arrival time by threshold on the peak of the ratio.[1] Baer and Kradolfer[3] improved the STA/LTA by using the envelope as characteristic function. There are numerous other approaches, including those based on higher-order statistics[21][11][12], autoregressive methods[15,19,22], shallow neural networks[5,6,8,23,24,28], methods that use wave polarization[4,20], and methods that use pickers in tandem[17,25]. Although the automated methods on phase picking have been extensive, the automated picking algorithms cannot currently match the accuracy of an experienced analyst.

In recent years, there has been truly astonishing progress within the field of artificial intelligence, most notably in the area of deep learning. Deep learning is a subdiscipline of machine learning that is based on training neural networks to learn generalized representations of extremely large data sets and has become state of the art in numerous domains of artificial intelligence, including computer vision, speech recognition and so on.[2,11,14] It has been recently introduced to seismology and has already shown considerable promise in performing various tasks including similarity-based earthquake detection and localization[18], generalized seismic phase detection[20,38], phase picking[29,37,39], first-motion polarity determination[20], detection of events in laboratory experiments[26], and predicting aftershock spatial patterns[7]. Although multiple methods on deep learning algorithm having made remarkable progress in phase picking using the large scale in seismic data, the network architecture still need a change for definite problems based different datasets[9,32,33,34].

In this paper, we focus on the application of P-wave arrival detection and time picking based on Chinese strong-motion records in 3 components using convolutional neural algorithm. We design a deep neural network based the architecture of fully convolutional network (FCN) which trained to learn the probability distribution of P wave from the known earthquake waveforms using the probabilities of manual picks p arrival time. In order to weak the overfitting with the limitation of small datasets, we generate ~149,000 normalized p-waveforms from 6776 three-component strong-motion records of 1798 earthquakes in Chinese Strong Motion Network through flipping and shuffling based the manual picks. We trained the FCN with ~120,000 normalized p-waveforms and confirmed the architecture of FCN and with the ~120,000 normalized p-waveforms from the validation dataset. And the trained network was tested on the testing dataset against with the STA/LTA+AIC method[35].

2. Data Processing and Augmentation

The dataset used in training the FCN is manually picked catalog of 1708 events containing 6776 exceeding 5-second P-wave seismograms in three components located throughout the China mainland (Fig.1). The events occurred between October 2007 to December 2017 and were recorded by the strong-motion acceleration stations with the sampling frequency of 200Hz. The magnitude of the events range from 1.1 to 8.0. The magnitudes are local magnitude M_L for events with $M < 4.5$ and surface wave magnitude M_W for lager events. Here we denote both types of magnitudes simply by M. The strong-motion P-wave seismograms consist of high and low signal-to-noise ratio (SNR) records, and with the range from 1.29 to 15500 (Fig.2). The SNR is calculated by the ratio of standard deviations of the five seconds following and the five seconds preceding the P arrival which picked by manual.

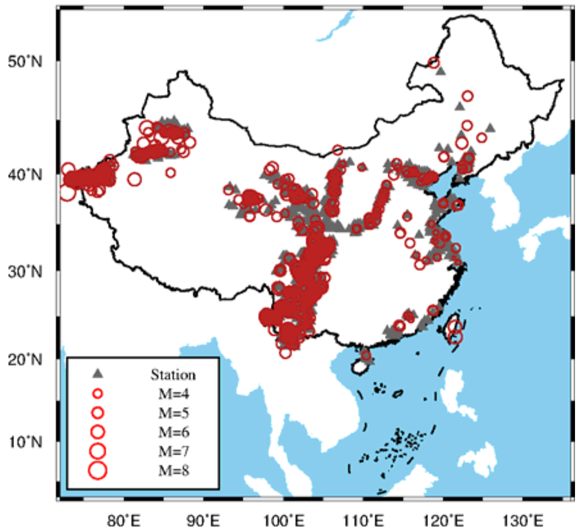

Fig 1. Distribution of epicenters and stations

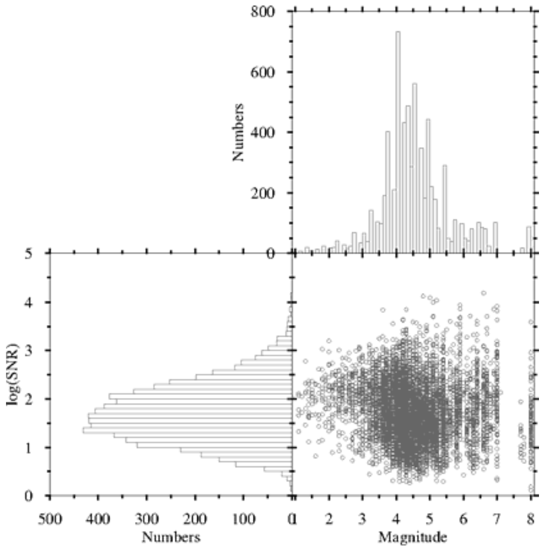

Fig 2. Distribution of magnitude and SNR

Manual picking P-wave arrival time picking are converted to the probability distribution of P-wave arrival as a Gaussian function with zero mean and a standard deviation of 0.1s (Fig.3d). The probability distribution of P-wave arrival as a Gaussian function allows the algorithm to reduce the errors and biases by manual picks. And according the peak and corresponding peak in the trace, the network can obtain an accurate and reliable result in P-wave arrival detection and time picking. The P-wave seismograms in three components and probability distribution of P-wave arrival are split into training, validation and testing dataset with the ratio of 8:1:1 by stratified sampling based on SNR.

The fully convolutional network for P-wave arrival time picking need an extremely large number of examples to prevent overfitting using the training dataset and enhance generalization. Our dataset is relatively small. To overcome the limitations with a small dataset, we adapt shuffle and flipping the P-wave seismograms to expand the number and quality of the data from data augmentation. The time window size of input for FCN is 20s. The time window moves 11 times within the time step of 1s from 15 second before P-wave arrival time in the trace and clipping the trace within random time step from 0 to 1 second basing on the beginning of time window. And the clipping trace was rotated 180 degree vertically in each component. Then the above 20-second trace was normalized by subtracting the mean of each component in the current time window trace, and dividing the subtraction of maximum and mean amplitude of each component time window trace (Fig 3a – d). After above data processing and augmentation, we finally expand the training, validation, testing datasets as the number of 119,174, 14,894, 14,916.

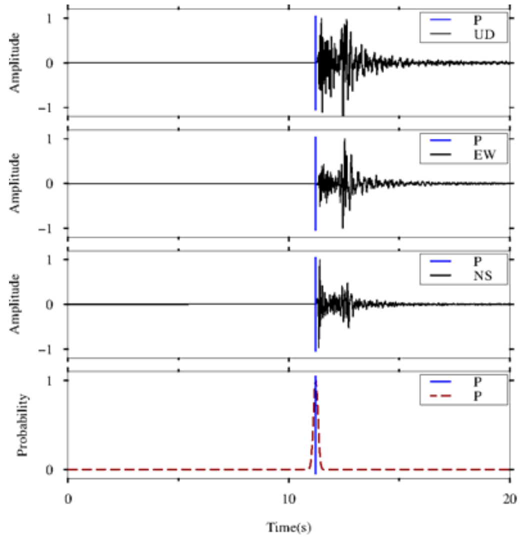

Fig 3. The example of input data and manual picking P-wave time.

3. Method

The fully convolutional network architecture (Fig.4) for P-wave arrival detection and time picking consists of an input layer with 20-second 3-component normalized P-wave seismograms (4001 samples), 2 resample stage, 3 down-sampling stage and 3 up-sampling stage. Inside each down-sampling stage process, the stage consists of convolution, leaky rectified linear units (Leaky RELU) and batch normalization (BN). Inside each up-sampling stage process, the stage goes through an extra max-pooling after the convolution layer. The resample stage is designed to extract and shrink the useful information from several components (channels) into one component (channel). The down-sampling stage process is designed to extract and shrink the useful information from P-wave seismograms to a few neurons. The up-sampling stage process expands and converts this information into probability of distribution of P-wave arrival time. The convolution kernel size is 10 points and convolution step is 4 points. The max-pooling kernel size is 2 points and step is 2 points. Therefore, the down-sampling and up-sampling stage's step is 8 points.

The outputs of FCN architecture for P-wave arrival detection and time picking are probability distribution of P-wave seismograms. The loss function is defined using mean square error (MSE) between the true probability distribution (p(x)) and predicted distribution (q(x)):

$$L(p,q) = \frac{1}{m}\sum_{i=1}^{m}(p_i(x) - q_i(x))^2 \tag{1}$$

where m represents the size of batch. The loss function measures the divergence between the two probability distribution. We convert the problems of P-wave arrival time picking as edge segmentation and we consider the MSE can be more sensitive for the divergence between the two probability distribution than cross entropy function. Therefore, we use MSE as loss function instead of cross entropy function.

Fig5 shows that the training and validation process. The FCN is trained by the loss function of MSE and AdamOptimizer with 0.001 learning rate. The loss function declines rapidly and the accuracy achieves 88%

through 2 epoch iterations on the training dataset. Through about 2000 epoch iterations, the rate of loss function verges to zero and the accuracy verges to 98% on the training and validation datasets. And we choose the 3042th checkpoint randomly to evaluate the performance of FCN on P-wave arrival time picking using the testing dataset.

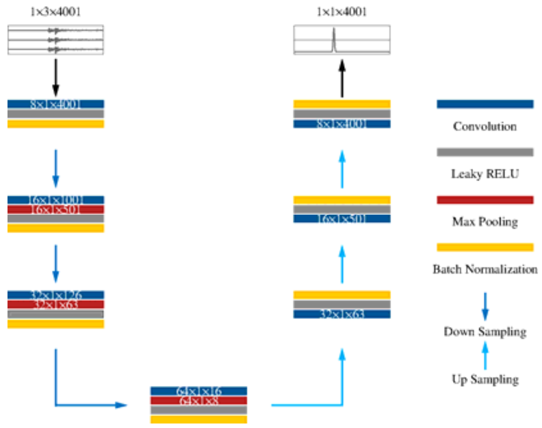

Fig4. The fully convolutional network architecture

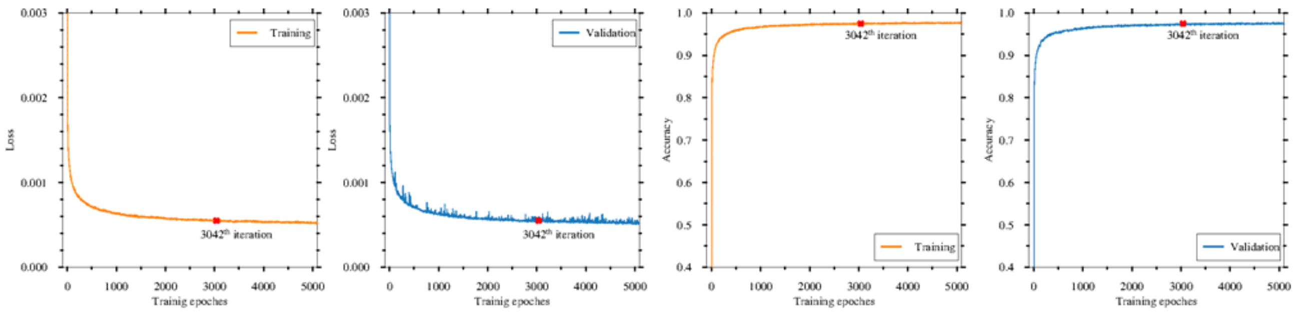

Fig5. The training and validation progress

4. Results

The evaluation parameters: precision, recall, accuracy, mean ($\mu_{|\triangle t|}$) and standard deviation ($\sigma_{|\triangle t|}$) of time residuals between manual picks and the FCN picks are applied to test the performance of FCN on P-wave arrival detection and time picking using the testing datasets.

$$Precision = T_P/(T_P + F_P) \tag{2}$$

$$\mathrm{Re}call = (T_P + F_P)/(T_P + F_P + F_N) \tag{3}$$

$$Acuracy = T_P/(T_P + F_P + F_N) \tag{4}$$

Where T_p is the number of true positives, F_P is the number of false positives, F_N is the number of false negatives. The precision, recall and accuracy are calculated by the number of true positives, false positives and false negatives. The positives are the reliable results which peaks of probabilities are larger than 0.5 as the reliable detection on P-wave arrival detection. The true positives are accurate results on P-wave arrival time picking as the time residuals within 0.1 second and the false positive are inaccurate results. The FCN pick is defined by the corresponding peak in the trace. The false negatives are the unreliable results which peaks of probabilities are less than 0.5. The mean ($\mu_{|\triangle t|}$) and standard deviation ($\sigma_{|\triangle t|}$) of time residuals between manual picks and the FCN picks are calculated based the positives.

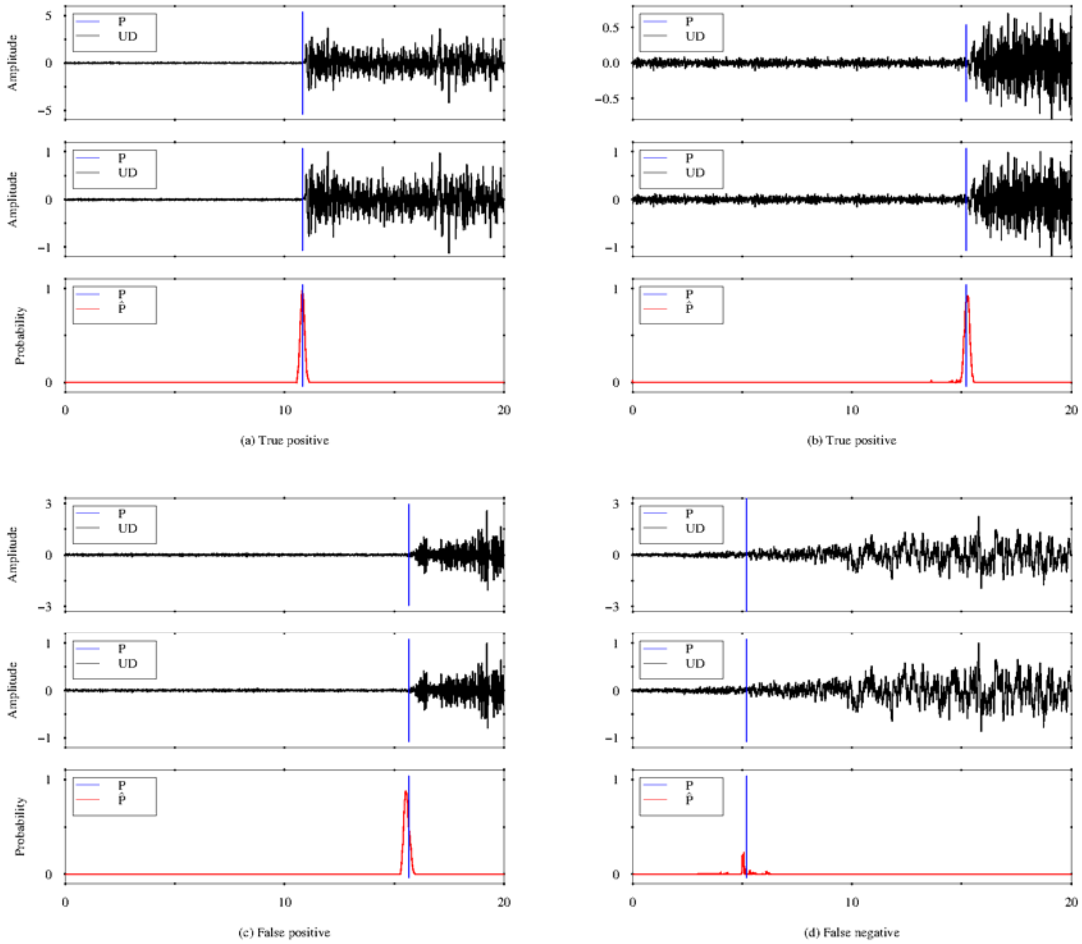

Fig6. The examples of FCN in the test dataset.

Fig6 a – c are the examples of true positives, false positives and false negatives picked by the FCN from the testing dataset. The examples of true positives and false positives show that the FCN has the reliable performance on P-wave detection with the strict peak threshold of 0.5. The examples of true positives show that the FCN has an accurate performance on picking P-wave arrival time within the time residuals of 0.1 second. Meanwhile, the SNR of true positives examples have the wide broad range from high to low SNR. And most of the false positives and false negatives are low SNR data. Table 1 is the performance of evaluation parameters using the testing datasets. The train FCN is tested against the short-term average/long-term average united Akaike Information Criterion (STA/LTA+AIC) method through the evaluation parameters.

Table 1 Evaluation parameters on the testing dataset

Evaluation parameters	**FCN**	**STA/LTA-AIC**
Accuracy	0.976	0.738
Recall	0.993	0.969
Precision	0.983	0.762
$\mu_{\lvert \triangle t \rvert}$(s)	0.026	0.252
$\sigma_{\lvert \triangle t \rvert}$(s)	0.084	0.797

The FCN achieves 0.976 accuracy, 0.993 recall, 0.983 precision, 0.026 second mean ($\mu_{|\triangle t|}$) and 0.084 second standard deviation ($\sigma_{|\triangle t|}$) of time residuals on the testing dataset. Each of the accuracy, recall and precision is larger than STA/LTA+AIC method and each of the time residuals' mean ($\mu_{|\triangle t|}$) and standard deviation ($\sigma_{|\triangle t|}$) is less than STA/LTA+AIC method. The evaluation parameters recall means that the performance of FCN on P-wave arrival time detection. The evaluation parameters Precision, mean ($\mu_{|\triangle t|}$) and standard deviation ($\sigma_{|\triangle t|}$) mean that the performance of FCN on P-wave arrival time picking among the detection results. The accuracy can represent the performance of FCN on P-wave arrival detection and time picking. The larger value of recall, precision and accuracy mean that the method have better performance on P-wave arrival detection and P-wave arrival time picking using the datasets. The less value of the time residuals' mean ($\mu_{|\triangle t|}$) and standard deviation ($\sigma_{|\triangle t|}$) show that the method has a more stable performance on P-wave arrival time picking using the testing dataset. This means that the FCN have a stable on P-wave detection and an accurate performance on P-wave arrival time picking using the testing datasets.

Fig7 is the accuracy between FCN and STA/LTA+AIC method with different SNR using the testing dataset. The testing dataset was divided as the criterion of logarithm SNR. The accuracy between FCN and STA/LTA+AIC method increase with the increase of logarithm. When the logarithm SNR is larger than 1.0, the accuracy of FCN has a stable and effective performance. However, the logarithm SNR is larger than 3.0, the accuracy of STA/LTA+AIC method has a stable and effective performance. And under the threshold of logarithm SNR 3.5, the accuracy of FCN is larger than STA/LTA+AIC method. These shows that the FCN performs more stably and effectively than STA/LTA+AIC in low SNR data.

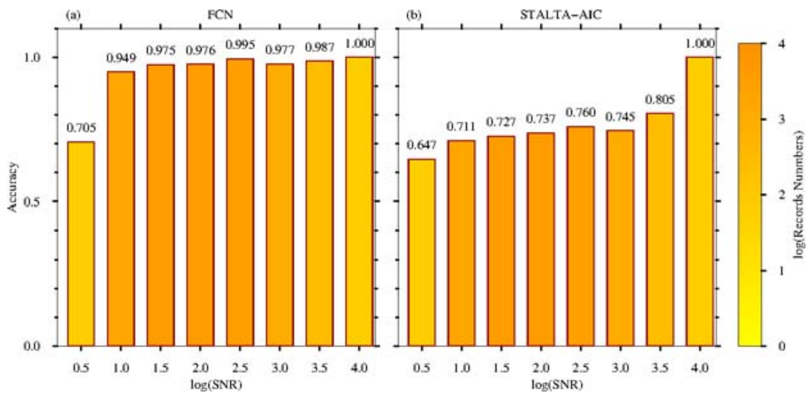

Fig7 The accuracy between FCN and STA/LTA+AIC method with different SNR

5. Discussion and conclusion

The trained FCN for P-wave arrival detection and time picking with nearly 120,000 normalized waveforms which were expanded from approximately 6700 three-component strong-motion records of 1708 earthquakes basing on China Earthquake Network Center Catalog during the period of 10/2007 ~ 12/2017. According to the performance of FCN using the training and validation datasets, the 3064th checkpoint was choosing to test the performance of FCN on the P-wave arrival detection and time picking using the testing dataset. The trained network achieves 97.8% accuracy on P-wave arrival time picking as manual picks within the time error of 0.1s and has 0.7% chance to miss the earthquake waveforms. The time residuals' mean and standard deviation of FCN picks on positives results shows that the performance of FCN is stable on P-wave arrival time picking.

Basing on evaluation parameters: accuracy, precision, recall, time residuals' mean and standard deviation using the testing datasets, the FCN has a more stable performance on P-wave arrival detection and more accurate performance on P-wave arrival time picking than STA/LTA+AIC method. According to the accuracy between FCN and STA/LTA+AIC method with different SNR, the SNR sections which are more stable and accurate performance on P-wave arrival detection and time picking of FCN and STA/LTA+AIC method was obtained in details. The FCN outperforms than STA/LTA+AIC with the SNR sections from 0.5 to 3.5 in logarithm. And most of the false positives and false negatives examples are low SNR data also promote this. Meanwhile, the FCN performs as the same as the STA/LTA+AIC method on P-wave arrival detection and time picking when the value of SNR is larger than 3.5 in logarithm. The FCN is more suitable than STA/LTA+AIC method in low SNR data.

Through analyzing vast false positives and negatives waveforms predicted by the FCN, there are approximately 60% waveforms are high noise level data which it is hard to pick the accurate P-wave arrival time. And approximately 30% waveforms which exists small continuous shaking before the catalog's earthquakes. These data are low SNR data in the performance of SNR. Meanwhile, there are about 10% waveforms are high SNR data. A small part of them are inaccurate manual picks. And the others may be solved by increasing the quality of the waveforms.

Although the FCN model provide an effective method for P-wave arrival detection and time picking, the FCN still exits the risk of overfitting and weak generalization by the limited variations using the input data. These problems are huge challenges for the application of FCN in the aspect of P-wave arrival detection and time picking. Nonetheless, the problems can be avoided by adapting the following measures: redesigning the architecture of network, import the new strong-motion records, short the time step of moving the time window, importing random noise (recorded noise) and so on. Our future work will focus on improving the FCN for testing the FCN on the strong-motion network.

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7. References

[1] Allen, R. V (1978): Automatic earthquake recognition and timing from single traces. *Bulletin of the Seismological Society of America,* 68**,** 1521-1532.

[2] Amodei, D., S. Ananthanarayanan, R. Anubhai, J. Bai, E. Battenberg, C. Case, J. Casper, B. Catanzaro, Q. Cheng & G. Chen (2016): Deep speech 2: End-to-end speech recognition in english and mandarin. In *International conference on machine learning,* 173-182.

[3] Baer, M. & U. Kradolfer (1987): An automatic phase picker for local and teleseismic events. *Bulletin of the Seismological Society of America,* 77**,** 1437-1445.

[4] Baillard, C., W. C. Crawford, V. Ballu, C. Hibert & A. Mangeney (2014): An automatic kurtosis-based P-and S-phase picker designed for local seismic networks. *Bulletin of the Seismological Society of America,* 104**,** 394-409.

[5] Dai, H. & C. MacBeth (1995): Automatic picking of seismic arrivals in local earthquake data using an artificial neural network. *Geophysical journal international,* 120**,** 758-774.

[6] Dai, H. & C. MacBeth (1997): The application of back-propagation neural network to automatic picking seismic arrivals from single-component recordings. *Journal of Geophysical Research: Solid Earth,* 102**,** 15105-15113.

[7] DeVries, P. M., F. Viégas, M. Wattenberg & B. J. Meade (2018): Deep learning of aftershock patterns following large earthquakes. *Nature,* 560**,** 632-634.

[8] Gentili, S. & A. Michelini (2006): Automatic picking of P and S phases using a neural tree. *Journal of Seismology,* 10**,** 39-63.

[9] Kong, Q., D. T. Trugman, Z. E. Ross, M. J. Bianco, B. J. Meade & P. Gerstoft (2019): Machine learning in seismology: Turning data into insights. *Seismological Research Letters,* 90, 3-14.

[11] Krizhevsky, A., I. Sutskever & G. E. Hinton (2012): Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems,* 1097-1105..

[12] Küperkoch, L., T. Meier, J. Lee, W. Friederich & E. W. Group (2010): Automated determination of P-phase arrival times at regional and local distances using higher order statistics. *Geophysical Journal International,* 181, 1159-1170.

[13] Küperkoch, L., T. Meier, A. Brüstle, J. Lee & W. Friederich (2012): Automated determination of S-phase arrival times using autoregressive prediction: application to local and regional distances. *Geophysical Journal International,* 188, 687-702.

[14] LeCun, Y., Y. Bengio & G. Hinton (2015): Deep learning. *nature,* 521, 436-444.

[15] Leonard, M. & B. Kennett (1999): Multi-component autoregressive techniques for the analysis of seismograms. *Physics of the Earth and Planetary Interiors,* 113, 247-263.

[16] Long, J., E. Shelhamer & T. Darrell (2015): Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition,* 3431-3440..

[17] Nippress, S., A. Rietbrock & A. E. Heath (2010): Optimized automatic pickers: application to the ANCORP data set. *Geophysical Journal International,* 181, 911-925.

[18] Perol, T., M. Gharbi & M. Denolle (2018): Convolutional neural network for earthquake detection and location. *Science Advances,* 4, e1700578.

[19] Rastin, S. J., C. P. Unsworth, R. Benites & K. R. Gledhill (2013): Using real and synthetic waveforms of the Matata swarm to assess the performance of New Zealand GeoNet phase pickers. *Bulletin of the Seismological Society of America,* 103, 2173-2187.

[20] Ross, Z. E. & Y. Ben-Zion (2014): Automatic picking of direct P, S seismic phases and fault zone head waves. *Geophysical Journal International,* 199, 368-381.

[21] Saragiotis, C. D., L. J. Hadjileontiadis & S. M. Panas (2002): PAI-S/K: A robust automatic seismic P phase arrival identification scheme. *IEEE Transactions on Geoscience and Remote Sensing,* 40, 1395-1404.

[22] Sleeman, R. & T. Van Eck (1999): Robust automatic P-phase picking: an on-line implementation in the analysis of broadband seismogram recordings. *Physics of the earth and planetary interiors,* 113, 265-275.

[23] Wang, J. & T. Teng (1995): Artificial neural network-based seismic detector. *Bulletin of the Seismological Society of America,* 85, 308-319.

[24] Wang, J. & T. Teng (1997): Identification and picking of S phase using an artificial neural network. *Bulletin of the Seismological Society of America,* 87, 1140-1149.

[25] Woollam, J., A. Rietbrock, A. Bueno & S. De Angelis (2019) Convolutional neural network for seismic phase classification, performance demonstration over a local seismic network. *Seismological Research Letters,* 90, 491-502.

[26] Wu, Y., Y. Lin, Z. Zhou, D. C. Bolton, J. Liu & P. Johnson (2018): DeepDetect: A cascaded region-based densely connected network for seismic event detection. *IEEE Transactions on Geoscience and Remote Sensing,* 57, 62-75.

[27] Zaremba, W., I. Sutskever & O. Vinyals (2014): Recurrent neural network regularization. *arXiv preprint arXiv:1409.2329,*.

[28] Zhao, Y. & K. Takano (1999): An artificial neural network approach for broadband seismic phase picking. *Bulletin of the* Seismological *Society of America,* 89, 670-680.

[29] Zhu, W. & G. C. Beroza (2019): PhaseNet: a deep-neural-network-based seismic arrival-time picking method. *Geophysical Journal International,* 216, 261-273.

[30] He X L, She T L, Gao F (2016): A new method for picking up arrival times of seismic P and S waves automatically. Chinese J. Geophys. (in Chinese), 59(7): 2519 - 2527

[31] Jiang Y R, Ning J Y (2019): Automatic detection of seismic body-wave phases and determination of their arrival

times based on support vector machine. Chinese J. Geophys. (in Chinese), 62(1):361 - 373

[32] LI Li, ZHANG Jianguo, LI Shengle (2018): Developenments of Research on Automatic Aftershock Recognition Technology. Journal of Seismolgical Reseach. (in Chinese),41(1): 1 -13

[33] LIU Hanlin, WU Qingju (2017): Developments of research on earthquake detection and seismic phase picking. Progress in Geophysics. (in Chinese), 32(3): 1000 -1007

[34] Liu J S, Wang Y, Yao Z X (2013): On micro-seismic first arrival identification: A case study. Chinese J. Geophys. (in Chinese), 56(5):1660 - 1666

[35] Ma Q, Jin X, Li S Y, Chen S W, Liao S R, Wei Y X (2013): Automatic P-arrival detection for earthquake early warning. Chinese J. Geophys. (in Chinese), 56(7): 2313 - 2321

[36] Sun Yin, Pan Suzhen, Liu Mingjun (2018): Seismic Phase Identification Associated with the Automatic Pickup Technology and Its Application. Earthquake Reseach in China. (in Chinese), 34(4): 606 -620

[37] Yu Z Y, Chu R S, Sheng M H (2018): Pick onset time of P and S phase by deep neural network. Chinese J. Geophys. (in Chinese), 61(12): 4873 - 4886

[38] Zhao M, Chen S, Dave Yuen (2019): Waveforms classification and seismic recognition by convolution neural network. Chinese J. Geophys. (in Chinese), 62(1):374 - 382

[39] Zhao M, Chen S, Fang L H, David A Yuen (2019): Earthquake phase arrival auto-picking based on U-shaped convolutional network. Chinese J. Geophys. (in Chinese), 62(8): 3034 - 3042.

