Predict arrival time of acoustic emissions on a laboratory fault without the velocity model

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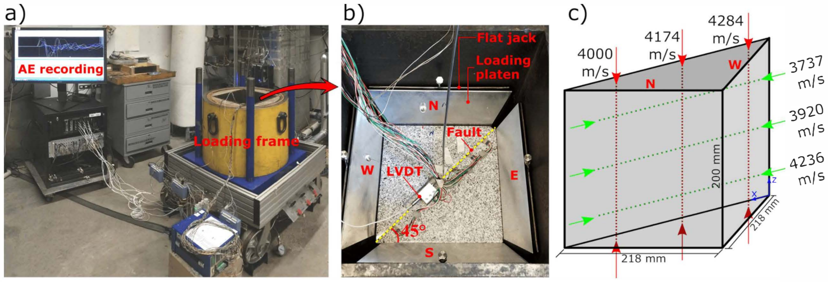
PRESENTED AT:

INTRODUCTION

Estimation of the arrival time of the seismic wave requires the knowledge of the velocity model from the hypocenter to the sensors. The velocity model can be obtained by tomographic imaging in the laboratory, even though in most cases isotropic models are assumed. Our earlier work showed that machine learning using an artificial neural network (ANN) can relocate acoustic emission (AE) on a laboratory fault without knowing the velocity model [1]. In this study, we demonstrate that the same ANN structure can be used in a reverse way, i.e., predicting arrival time for AE events with known locations.

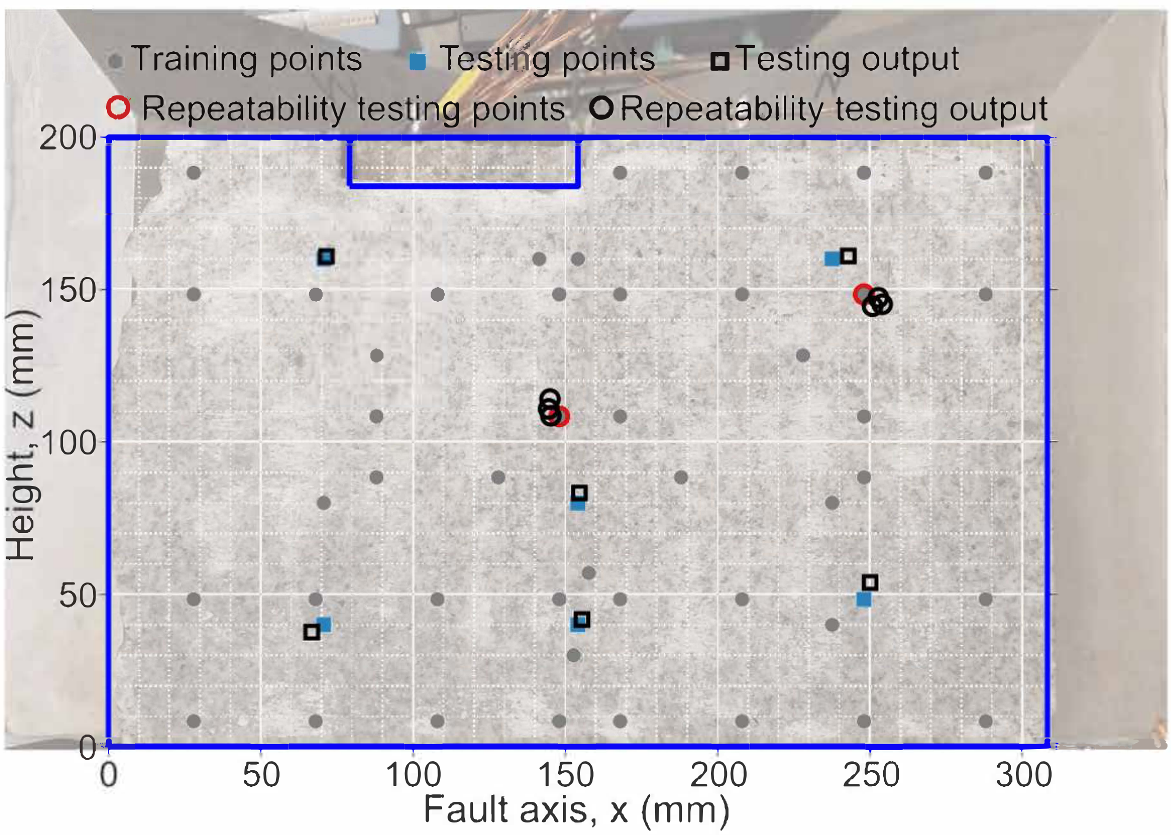
EXPERIMENTAL SETUP



The experimental setup: a) The loading apparatus and AE recording system, b) the specimen assembly that consists of two halves of the rock (218 mm x 218 mm x 200 mm), separated by the laboratory fault. The loading platens are actuated by flat jacks, and AE sensors (PTZs) are embedded in platens on the North (N) and West (W) sides of the block. The training data was obtained on the NW block before the experiment. (c) The anisotropic velocity structure indicated by several P-wave velocity measurements, which makes conventional relocation and forward modelling difficult.

Training data: We create 56 AEs by breaking 0.7 mm diameter pencil leads [2] at known locations on the laboratory fault surface (NW block) before the rock assembly is put together for testing. These events are spread over the entire fault surface to ensure good spatial coverage. We pick the P-wave arrival time with Akaike information criterion (AIC) [3].

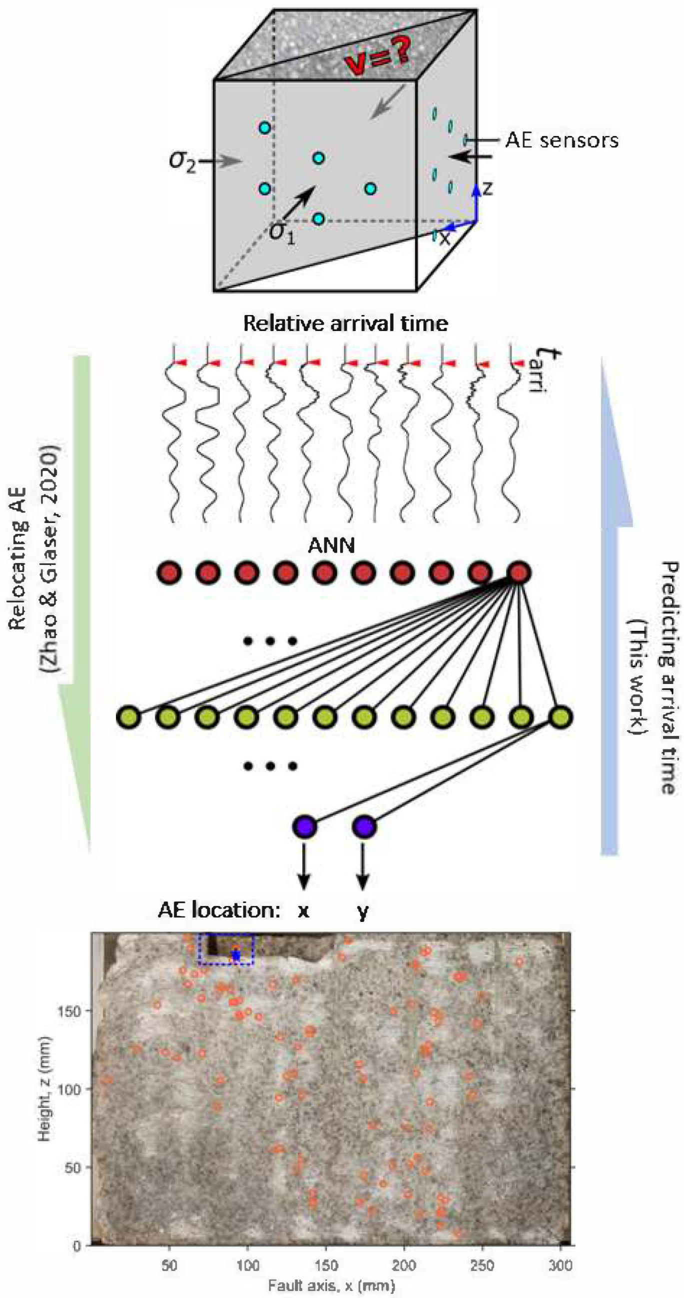
In Zhao and Glaser (2020) [1], the ML models using the relative P-wave arrival time (t_{rel}) as the input and AE source locations (x, z) as the output. The relative P-wave arrival time was calculated relative to AE sensor PTZ#1. The figure below shows the training data and test results overlying the laboratory fault. This result demonstrates the capacity of our method in accurately relocating AEs on the laboratory fault with <4 mm accuracy [1].



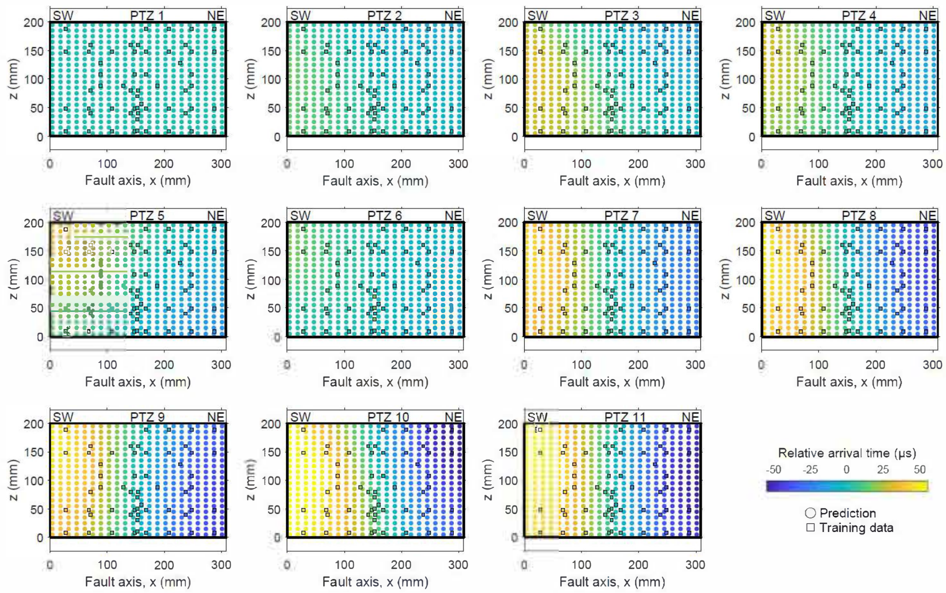
Artificial neural network (ANN) structure: In this work, we use the known AE location (x, z) as the input and t_{rel} as the output. The ANN structure is reversed correspondingly. All the data points shown in the figure above are used for this study.

The ANN structure consisting of the following layers: (1) layer 0, the input layer that takes (x, z) as input; (2) layer 1, the hidden layer that consists of 12 neurons; and (3) layer 2, the output layer that has 10 neurons and outputs the t_{rel} for AEs on sensors PTZ#2-10. In order to avoid overfitting problems, we train an ensemble of 50 ANNs with the same architecture for 100 epochs and average their outputs. Also, we use the ten-fold cross-validation to examine the accuracy.

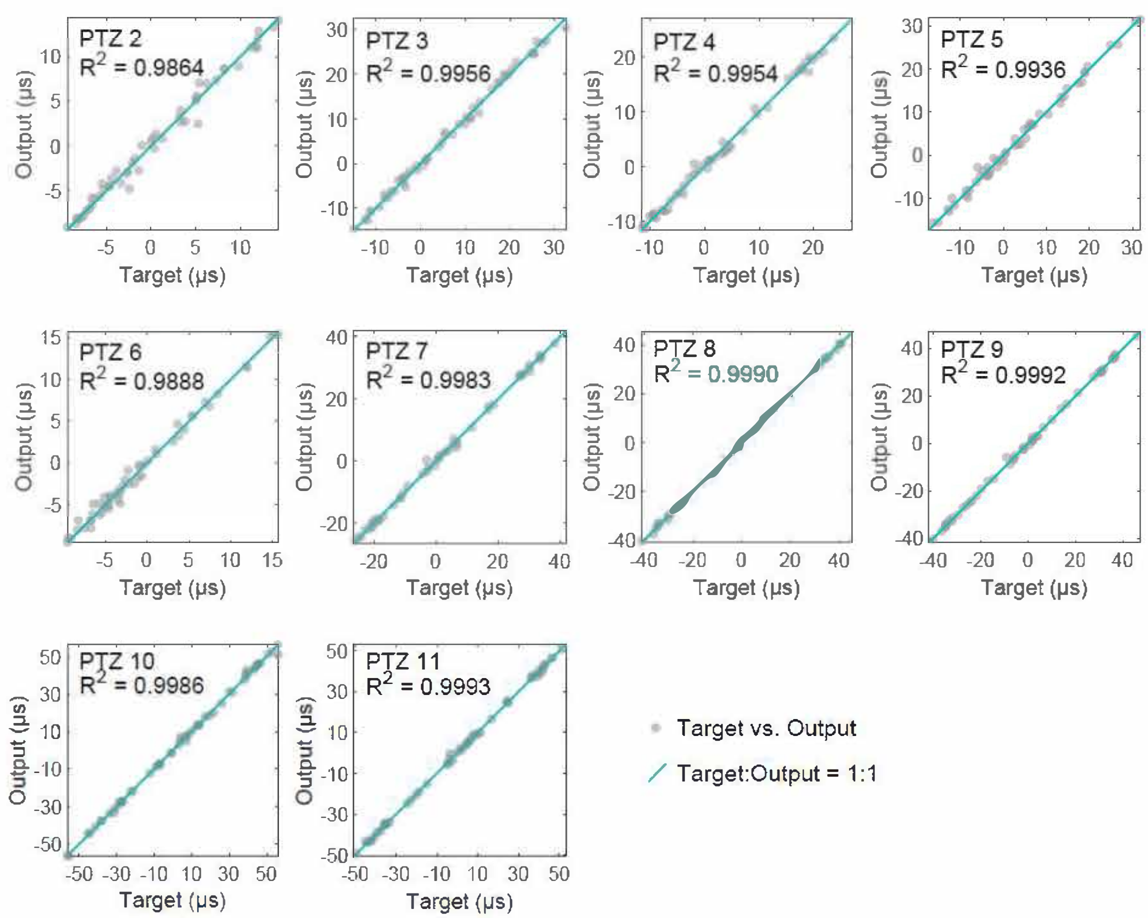
MACHINE LEARNING METHOD



RESULTS



(Click the figure to enlarge) Predicted relative arrival time for AE events on the entire laboratory fault for each sensor (all zero for PTZ#1 as it is the reference sensor for relative arrival time). With the proposed method, we can predict the relative arrival time of any AE events at any locations on the laboratory fault surface.



Training results for relative arrival time prediction for sensors PTZ#2-10. The predictions from the ANN show a high degree of agreements with the ground truth.

IMPLICATIONS AND FUTURE WORK

The proposed approach estimates arrival time without forward modelling, and it may be used to predict the arrival time of events at any locations on the fault surface, providing virtual ray-path coverage that may facilitate improved tomographic inversion. Moreover, this method is not restricted to manually created training data. Strong earthquake seismograms could be used as the training data, and our approach could be applied to natural/induced earthquakes, for situations where arrival time data are missing due to, for example, malfunctioned stations and/or weak seismic signals.

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ABSTRACT

Estimation of arrival time of seismic wave requires the knowledge of the velocity model between the hypocenter to the sensors. The velocity model can be obtained by tomographic imaging in the laboratory, even though in most cases isotropic models are assumed. Our earlier work showed that machine learning using artificial neural network (ANN) can relocate acoustic emission (AE) on a laboratory fault without knowing the velocity model (*Zhao and Glaser, 2020, Rock Mech Rock Eng, 53, 2053–2061*). In this study, we demonstrate that the same ANN structure can be used in a reverse way, i.e., predicting arrival time for AE events with known locations. This approach estimates arrival time without forward modelling, and it may be used to predict arrival time of events at any locations on the fault surface, providing virtual raypath coverage that may facilitate improved tomographic inversion. Moreover, this method could be applied to natural earthquakes, for situations where arrival time data are missing due to, for example, malfunctioned stations and/or weak seismic signals.

REFERENCES

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