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Relocating acoustic emission in rocks with unknown velocity structure with machine learning

Qi Zhao* and Steven D. Glaser
University of California, Berkeley
*qi.zhao@berkeley.edu

Introduction

Inversion of hypocenters is the first and most fundamental step in the study of seismic activities. In this study, we prove that machine learning (ML) methods including artificial neural networks (ANNs) and support vector machines (SVMs) can relocate hypocenters of acoustic emissions (AEs) without *a priori* knowledge of the velocity structure [1].

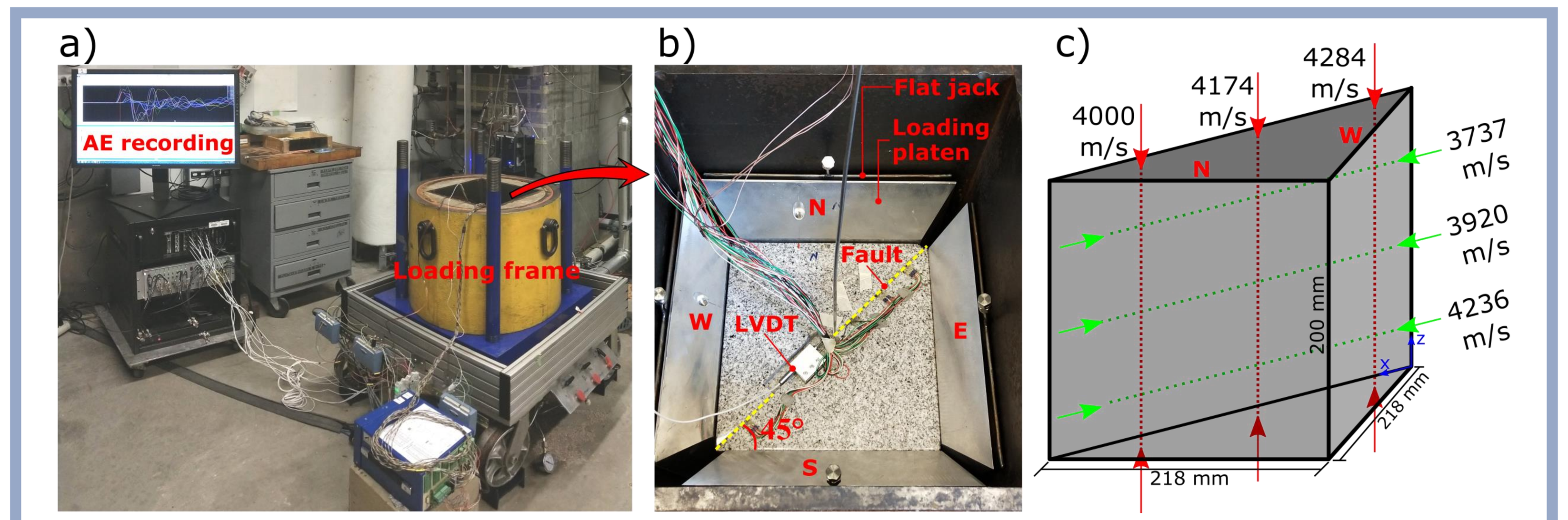
Conventional method: tomography scan with additional sensor arrangement, then iterative source location inversion.

Our method: create the training data with no additional sensor arrangement, train the ML model, and deploy the model.

Problem statement

Relocating acoustic emission in rocks requires solving the non-linear relation between the travel time and hypocenter locations, which is heavily dependent on the knowledge of the medium properties, most importantly the velocity structure. Numerous methods have been applied to relocate earthquake hypocenters, and the most widely used approaches are the travel time inversion methods [2,3]. These methods center around the goal of solving the non-linear relation between the travel time and the hypocenter location, which requires predefined velocity models of the medium. The accuracy of the relocation heavily replies on the quality of the velocity model. Laboratory samples are often assumed to be isotropic, and constant velocity models are usually used. Relocating AE using conventional relocation methods becomes a difficult task when the rock has velocity anisotropy. It requires tomographic inversion of the sample to establish a velocity model, and then iterative inversion for relocation, which is time consuming and computationally expensive.

Methods



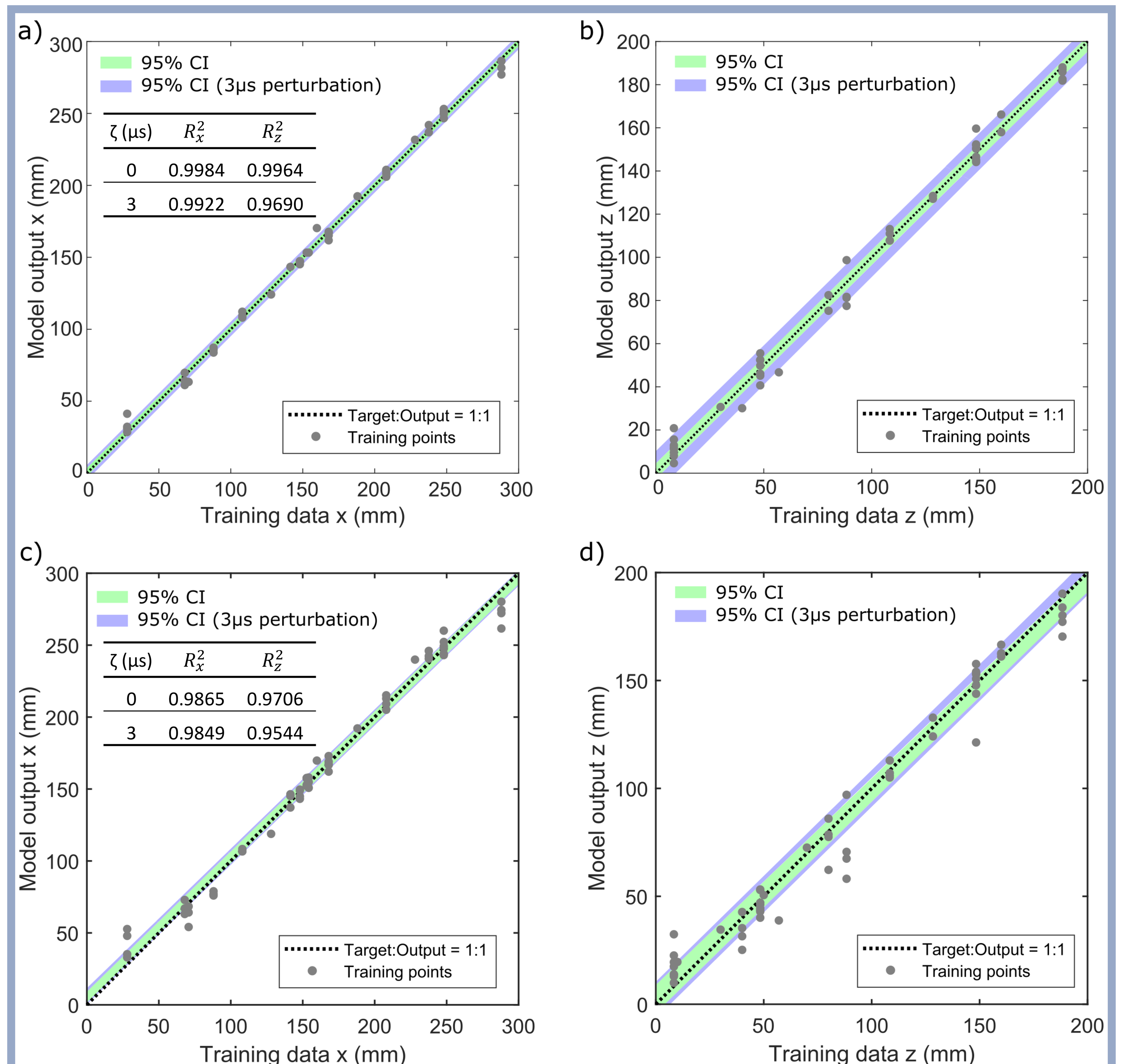
Experiment setup. a) The loading apparatus and AE recording system, b) the specimen assembly that consists two halves of the rock, separated by a fault. The loading platens are actuated by flat jacks, and AE sensors are embedded in platens on north (N) and west (W) sides of the block. We conducted a right-lateral shear slip on the laboratory fault, with approximately 15 mm of slip distance at a fault normal stress of 10 MPa.

Training data: We create 56 AEs by breaking 0.7 mm diameter pencil leads at known locations on the fault surface [4], before the rock assembly is put together for testing. These events are spread over the entire fault surface to ensure a good spatial coverage. We pick the P-wave arrival time with Akaike information criterion (AIC) [5]. The ML models using the relative P-wave arrival time (t_{rel}) as the input and AE source locations (x, z) as the output.

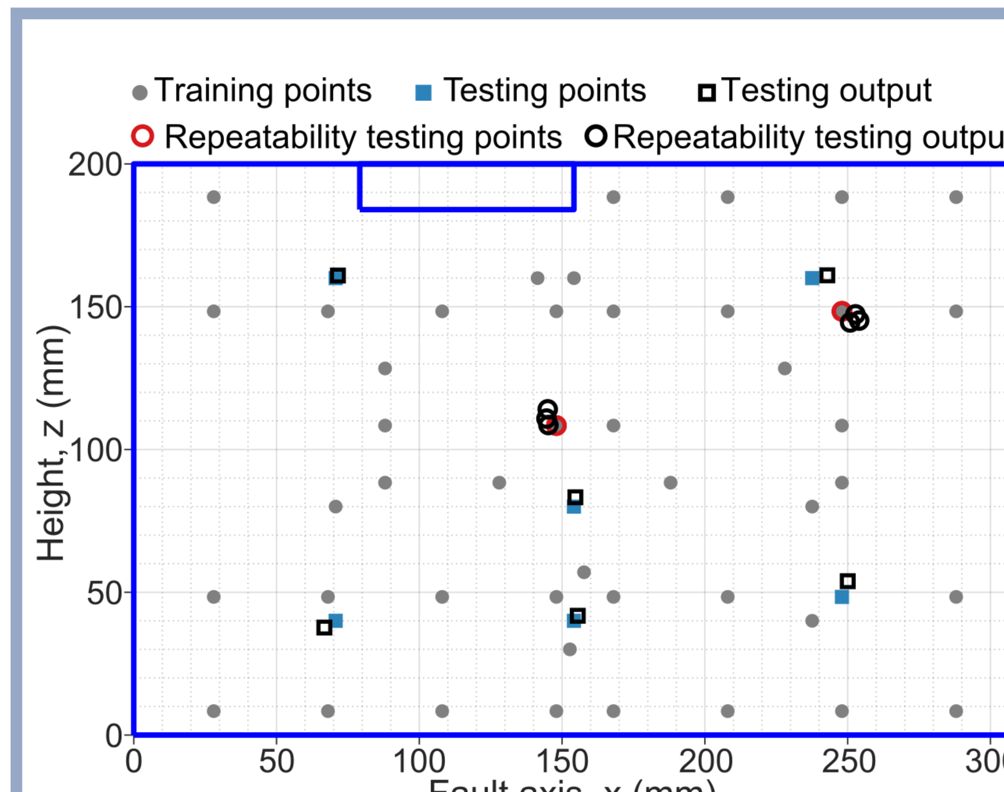
Method 1 ANN: The ANN structure consisting of the following layers: (1) layer 0, the input layer that takes t_{rel}; (2) layer 1, the hidden layer that consists of 12 neurons; and (3) layer 2, the output layer that has two neurons and outputs the AE hypocenter coordinates on the fault surface (x, z). We train an ensemble of 50 ANNs with the same architecture for 100 epochs and average their outputs.

Method 2 SVM: We use the ε-insensitive support vector regression method [6] and hyperparameters including (1) the kernel scale constant (kernel type: linear), (2) the value of ε-insensitivity, and (3) the regulation parameter are optimized with an exhaustive grid search.

Validation: We assess the accuracy of the ML models with the ten-fold cross-validation method, which is suitable for the relatively small sized data set. To examine the sensitivity to arrival picking quality, random perturbation (ζ) of 3 µs is added to the arrival time in the training data set. The perturbed arrival times are then evaluated using the ML models. We list here the goodness of fit (R_x^2 and R_z^2), for x and z, respectively.



Training and testing results of the ML models. a) and b) Training and sensitivity test results of the generalized ANN model for x and z, respectively. c) and d) Training and sensitivity test results of the SVM model for x and z, respectively. Model outputs are plotted against ground true (i.e., targets) in the training data, and 95% confidence intervals (CI) are shown.

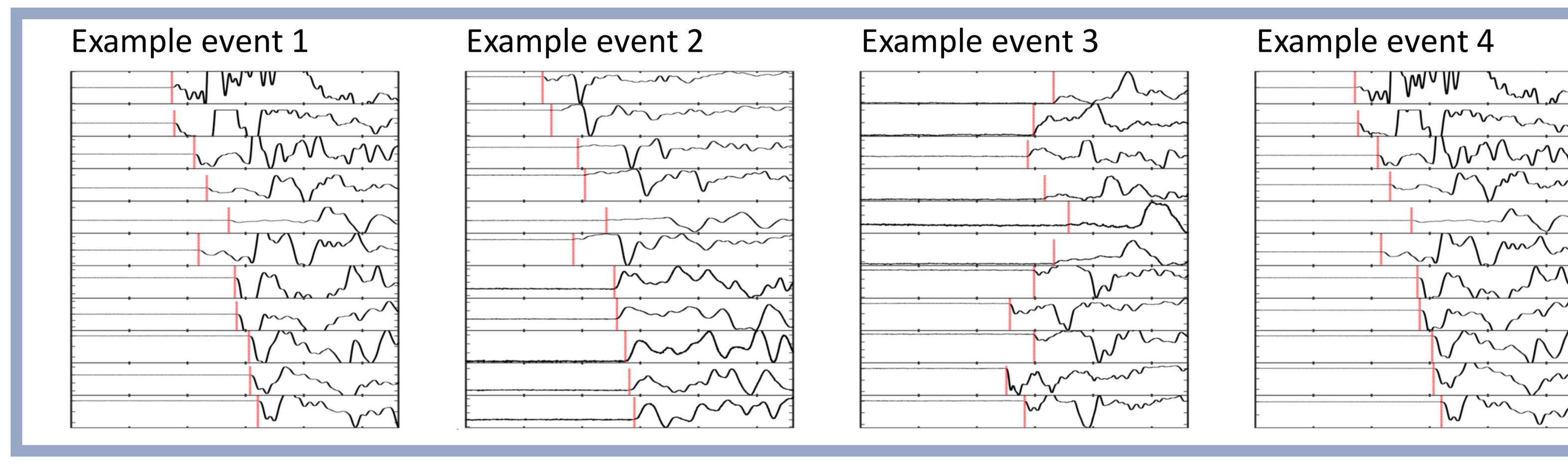


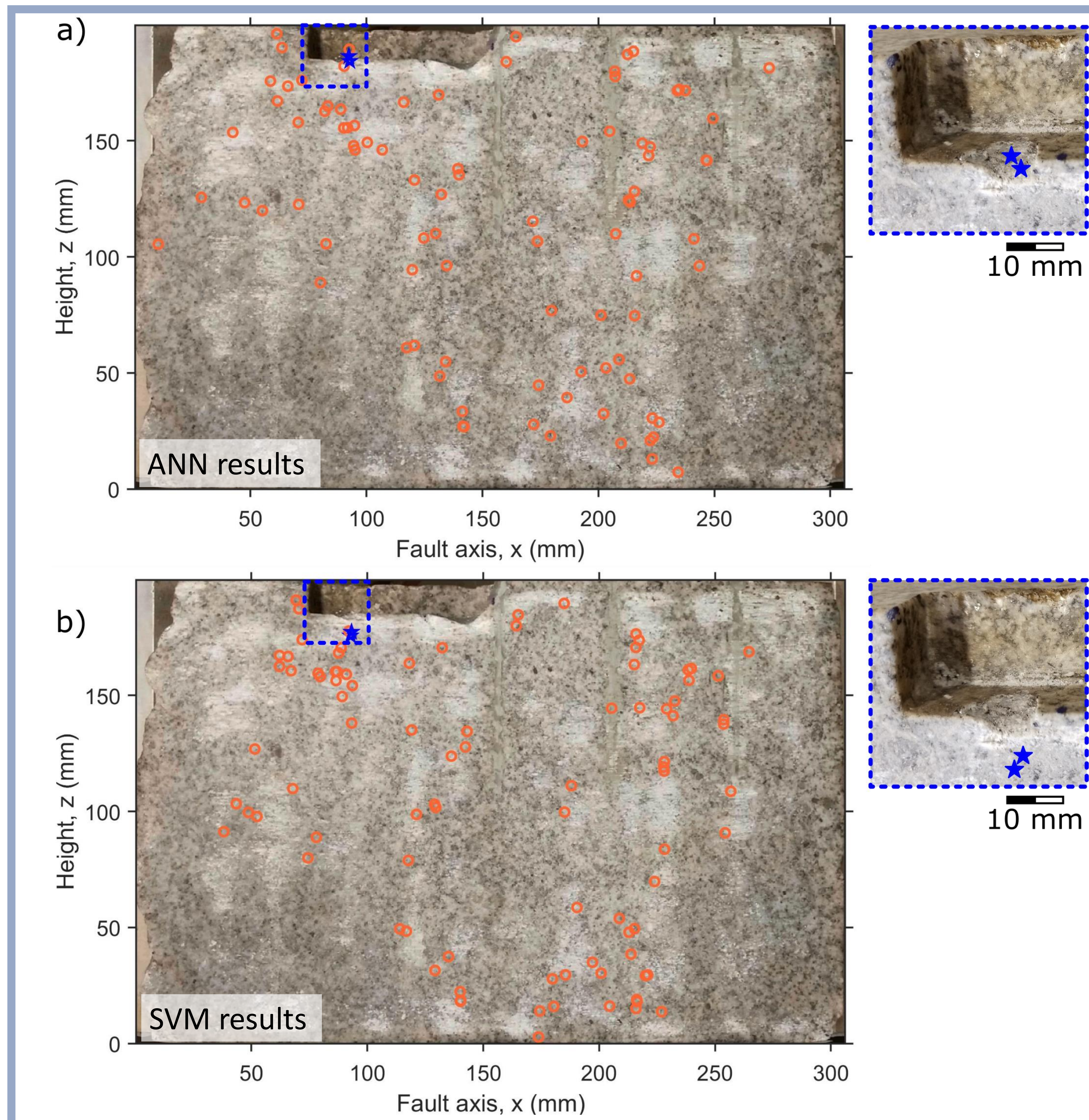
The ANN model achieved better accuracy than the SVM model. Its RMSEs of the ten-fold cross-validation are 1.7 mm and 3.9 mm, for x and z, respectively.

We evaluate the ML models on AEs created at two known locations and each with four repetitions. The absolute errors on the repeatability testing data are 1.7 mm and 2.8 mm, for x and z, respectively.

Results

During the test, 524 AEs are recorded. The signal quality varies as the event location and energy differ significantly. As a result, 96 events have clear onset in all the channels and the arrivals can be confidently picked. We then use the relative arrival time derived from the picked arrivals as input to the ML models to relocate these events.





AEs are associated to the breakage/rubbing of pronounced asperities. They distribute following vertical stripes, which are ridges created by sandblasting passes. High spatial concentration of AEs is found at the upper-left quadrant of the surface. This area experienced most damage, and the two strongest AEs show close correspondence to a ~10 mm chipping at the edge.

Conclusion

This study suggests that ML methods can provide effective and accurate approaches for relocating seismic events in a medium with unknown velocity structures. Our methods may expand the application of AE monitoring as they solve the problem of relocating acoustic emission on a surface with unknown material properties.

References: **[1]** Zhao, Q. and Glaser, S. D.(2019). Relocating acoustic emission in rocks with unknown velocity structure with machine learning, *Rock mechanics and rock engineering*. **[2]** Geiger, L. (1912). *Bull. St. Louis Univ*. 8, 56–71. **[3]** Aki, K., and Lee, W. H. K. (1976). *Journal of Geophysical Research*, 81(23), 4381– 4399. **[4]** Hsu, N. N., Simmons, J. A., and Hardy, S. C. (1978). Proceedings of the ARPA/AFML Review of Progress in Quantitative NDE, September 1976–June 1977. 31. **[5]** Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle, in 2nd International Symposium on Information Theory, B. Petrov and F. Csaki (Editors), Budapest Akademiai Kiado, 267–281. **[6]** Vapnik, V. *The Nature of Statistical Learning Theory.* Springer, New York, 1995.