Passive seismic monitoring empowered by AI

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Summary

Seismic Passive seismic monitoring is critical for many industries, helping them develop effective risk mitigation strategies. By quickly and accurately detecting earthquakes in near real-time, these strategies can be much more responsive. Additionally, it provides valuable insights into operational effectiveness, guiding future plans. Traditional methods of processing seismic data have limitations however, AI-enhanced processing has significantly improved the quality of automatic earthquake catalogs. Our research, including the findings presented here, demonstrates that a significant portion of AI-generated events are as good as, or even better than, those processed manually. These breakthroughs have challenged traditional approaches to evaluating automated systems. This paper explores our journey with AI-enhanced seismic data processing and how it can empower automatic performance benchmarking and improve quality of seismic catalogs.

Method

Detecting seismic phase arrivals traditionally relied on finding impulsive changes in the raw data using methods like short-term/long-term averages (STA/LTA). While these methods are computationally fast, they struggle with impulsive noise. Additionally, they require extensive adjustments for each network and channel to achieve optimal performance. Even with fine-tuning, these methods still generate results that demand significant manual review to achieve a high quality final result.

Our initial AI based implementation at Nanometrics involved using Support Vector Machines (SVM) for phase picking (Reynen 2018). While SVMs showed promise in some cases, their performance was inconsistent. More recently, the field of passive seismic monitoring has seen a surge in advancements using neural networks. Pioneering models like EQTransformer (Mousavi et al., 2020), PhaseNet (Zhu et al., 2018), and PickNet (Wang et al., 2019) have paved the way for significant progress. Our approach builds upon these foundations, incorporating additional optimizations and leveraging the vast datasets collected by both public seismic arrays and Nanometrics' private installations. This allows us to create more accurate results.

Our model was trained on a rich dataset exceeding 2 million observations. This data encompasses a wide variety of monitoring applications, earthquake magnitudes, and event-station distances (Figure 1). Because data quality is crucial for model accuracy, significant effort was invested in cleaning the training dataset. This involved both automated and manual techniques to remove outliers, correct errors, and ensure consistency.

Furthermore, to optimize model performance, we implemented a hyper-parameter optimization routine to maximize model precision and recall for identifying seismic events.

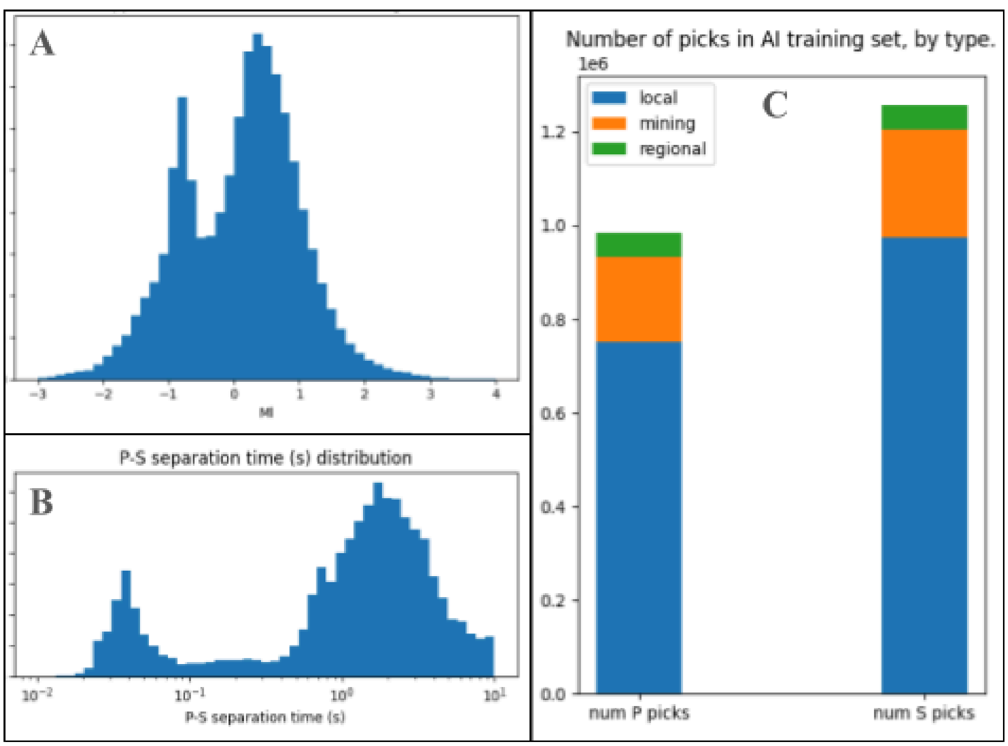

Figure 1: Illustrates the phase pick observations employed in neural network (NN) training. A histogram showcasing the event local magnitude Ml (a), a histogram representing the P-S phase separation in seconds as a proxy for event-station distance (b), and a distribution of P- and S-phase picks categorized by the type of monitoring array where they were captured (c).

Results

Figure 2 shows the comparison of results obtained from the processing methods mentioned above. All representations maintain uniformity in the event catalog, array selection, data availability, velocity model, and relocation process; differing solely in the input phase picks. A discernible trend towards enhanced clustering of event locations and improved comprehensibility of the event catalog is evident across all displays. Notably, the event locations generated by the neural network (NN) method begin to match or even surpass those derived from manual processing. This trend is attributed to the presence of human bias, which inevitably influences pick precision and is less pronounced in the AI implementation.

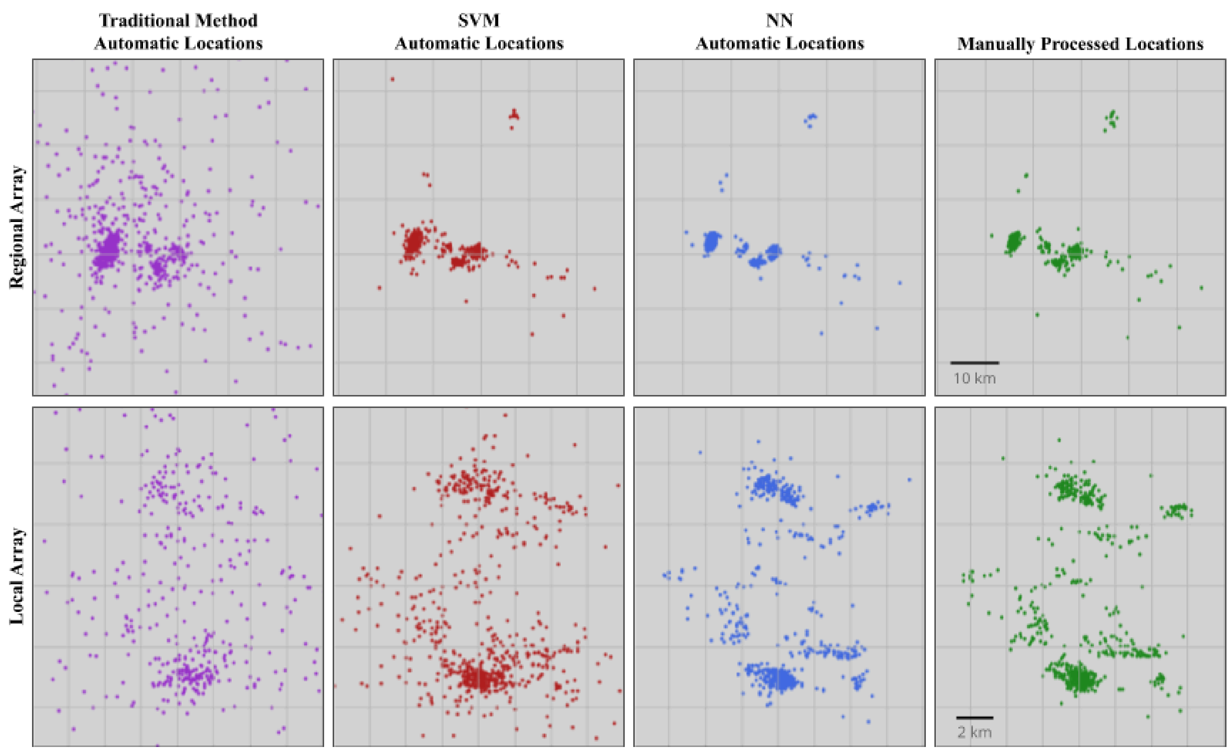

Figure 2: Map comparisons illustrating automatic event locations derived from various methods: purple for the traditional automatic method, red for SVM (Support Vector Machine) automatic method, blue for our Neural Network (NN) automatic method, and green for manually processed events. These comparisons are presented for a regional seismic monitoring array (top row) and a local array (bottom row).

CONCLUSIONS

We present the outcomes of our recent advancements and practical applications of AI-based technology in passive seismic monitoring. Our globally trained convolutional neural network (NN) has demonstrated exceptional performance. We have observed remarkably high-quality automatic event solutions, with a significant proportion of these solutions matching or surpassing the quality of manually processed events. Our objective is to persist in refining these methods and exploring novel approaches to further enhance automatic performance in near real-time passive seismic monitoring applications, both at regional and local scales.

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