Experimental Validation for Early Earthquake Detection Using Transfer Learning

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Abstract: We apply transfer learning with an LSTM-attention model, trained on simulated earthquake SOP data and tested on experimentally emulated data over a 38 km deployed fiber link, achieving 98% accuracy in early earthquake detection.

1. Introduction

Earthquake Early Warning Systems (EEWSs) are crucial to mitigate the devastating humanitarian and economic consequences, particularly in densely populated areas. The first development of EEWS dates back to the 1960s, when Japan pioneered the UrEDAS system, designed to provide railroad warnings by utilizing seismic stations to detect ground motion induced by the arrival of primary earthquake wave that precedes the destructive surface wave by tens of seconds, allowing warnings to be issued before severe shaking occurs [1]. However, the global density of seismic stations is low, leading to a poor spatial sampling analysis of seismic activity. Moreover, the cost of deploying and maintaining a larger, denser, and homogeneous network of these stations pose great economic challenges, making this solution impractical even for highly developed nations [2]. Therefore, in [3] and [4], we presented a novel approach to exploit the entire terrestrial traffic-carrying optical fiber network as a sensing and epicenter localization grid for early earthquake detection. This Machine Learning (ML)-driven approach leverages distributed polarization sensing to detect primary wave over vast geographical areas without requiring dedicated dark fibers or expensive equipment, unlike other fiber sensing techniques like Distributed Acoustic Sensing [5] and Interferometric Techniques [6]. The ML model used, accurately detected the primary wave of a real M4.3 earthquake that struck in the Modena region in Italy and provided urban areas near the epicenter an early warning with a time window of 21 seconds to take earthquake countermeasures, 35 seconds for areas further away, and up to 57 seconds for the most distant regions. The simulated State-of-Polarization (SOP) data extraction was done by utilizing a python-based Waveplate model [7], which segments an optical fiber into small sections or plates to capture the impact of internal birefringence on SOP alterations. Any deviations from the expected internal behavior are attributed to external events. Due to random orientation of plates in each simulation and after coupling the real earthquake ground displacement values, extracted from the National Institute of Geophysics and Volcanology in Italy [8], as strain values into the fiber cable, we were able to extract a large set of SOP evolutions for the Modena earthquake. ML model testing showed a 98% accuracy in detecting the primary wave based on the pattern of polarization changes. In this manuscript, we use the LSTM-attention ML model utilized in our latest work [9], which was trained to distinguish between simulated data of two external events: the M4.3 Modena earthquake and a car passage, even under noisy conditions where the signals overlap. The novelty here lies in leveraging transfer learning, where the LSTM-attention model is fine-tuned on a smaller laboratory-based emulated set of polarization data after propagation over 38 km of fiber cable deployed in the city of Turin, Italy. This approach not only leverages the advantages of the pre-trained model but also enables accurate earthquake early detection despite real propagation challenges. In Section II, we present the experimental design, while in Section III, we demonstrate the ML model testing results. Finally, Section IV concludes the discussion.

2. Experimental Design

The system replicates SOP stokes previously generated using the python-based Waveplate model by utilizing a tunable laser, operating at a wavelength of 1550 nm and an output power of 6 dbm to generate the optical signal. The optical signal is then fed into an optical scrambler composed of seven plates with random orientations, which are adjusted according to the voltage applied to each plate to match the target SOP provided to the scrambler. The scrambled signal is subsequently captured by a polarimeter, which measures the SOP and provides feedback to the scrambler, indicating the difference between the measured and target SOP. The scrambler then adjusts new plates' orientations, applying a minimization function to gradually align with the target SOP. This Back-to-Back (B2B) setup corresponds to the path 1 in Figure 1.

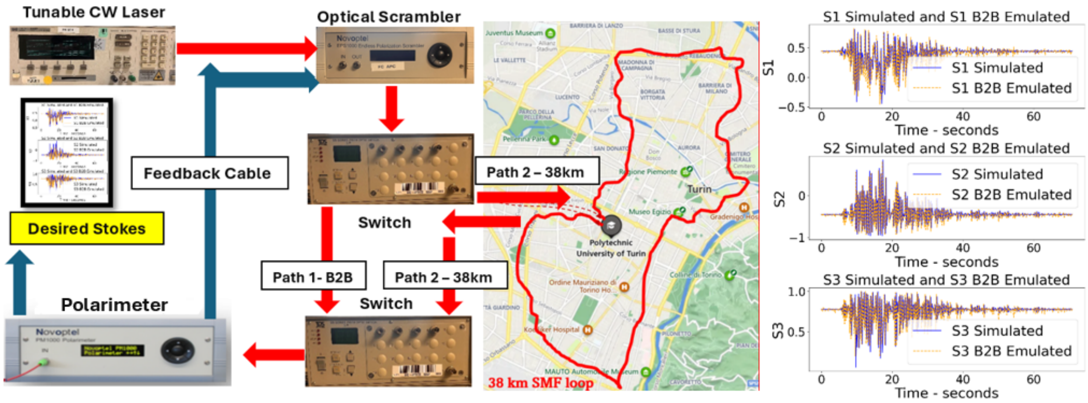

Fig. 1: Lab Setup to Compare Simulated, B2B-Emulated, and Propagated B2B Stokes induced by Strain Values from the M4.3 Earthquake that struck on 23 of May 2012 in the Region of Modena, Italy

Simulated and B2B emulated stokes shown on the right of Figure 1 exhibit an excellent match, indicating that the scrambler is well-trained to target the desired SOP evolution induced by the earthquake strain values. For path 2 in Figure 1, the same set of voltages is applied to the scrambler's seven plates to replicate the B2B emulated stokes, allowing them to propagate under real-world conditions over 38 km of single-mode-fiber (SMF) deployed in the city of Turin, Italy. This configuration allows us to fine-tune our pre-trained and validated ML model to assess the model's performance on the propagated B2B stokes under real-world propagation challenges, ensuring that the model can still accurately detect the primary earthquake wave. To reduce complexity and minimize computational time, we choose to calculate State of Polarization Angular Speed (SOPAS) instead of the full SOP [10]. This calculation allows us to work with a single parameter instead of three (S1, S2, and S3), making it easier for the ML model to detect invariant patterns from SOPAS evolutions.

3. ML Model Results

The pre-trained model employs a deep learning architecture that combines Long Short - Term Memory layer (LSTM) [11] and an Attention Mechanism [12]. The SOPAS inputs are analyzed by four LSTM layers, which return the full sequence of outputs to further process temporal dependencies, improve model's ability to identify complex patterns, and help refine the sequence representations. The attention mechanism then dynamically weighs the importance of each time step in the LSTM outputs sequence through a dot product operation after generating attention probabilities using softmax activation. This allows the model to focus on the most informative parts of the sequence and distinguish between different seismic waves (primary, secondary, and surface waves). The model was initially trained on a simulated SOPAS dataset to learn the complex patterns of SOPAS alterations caused by the seismic events. In this study, we apply transfer learning after leveraging the knowledge from the pre-trained model and fine-tune it on a smaller emulated SOPAS dataset propagated over 38 km of fiber cable, allowing the model to adapt to real-world conditions with minimal additional training. The fine-tuning was performed over 10 epochs, allowing the model to adapt to specific characteristics of the propagated dataset while preserving the knowledge gained previously from the larger simulated data. This transfer learning approach not only improves model's performance but also significantly reduces the need for large-scale labeled data during training. This study demonstrates how transfer learning enables the pre-trained model to adapt to new data, transitioning from a simulated to an in-field and laboratory-based concepts. Even though there was some discrepancy between the emulated B2B and the propagated B2B SOPASs as shown in one of the examples left of Figure 2, the model still achieves outstanding performance. For the emulated propagated data, the model achieves 98% accuracy in detecting the primary wave, with an F1 score of 98%, recall of 97%, and precision of 98%. The confusion matrix in the middle of Figure 2 illustrates the model's high accuracy in detecting various wave types, including "No Earthquake (No EQ)," "Primary Wave (P Wave)," "Secondary Wave (S Wave)," and "Surface Wave (Surface Wave)." Out of 2156 primary wave events, the model correctly detected 2089, with minimal misclassifications: 19 instances were incorrectly labeled as No Earthquake, and 48 were misclassified as secondary waves. The model also performed exceptionally well in identifying surface waves, correctly detecting 11017 out of 11200 instances. Finally, the model demonstrates its ability to detect multiple seismic events, accurately identifying the primary wave within one second (right of Figure 2). The results highlight the effectiveness of transfer learning, fine-tuned over 10 epochs, in adapting a pre-trained model to new real-world dataset, achieving high accuracy with reduced data and training effort.

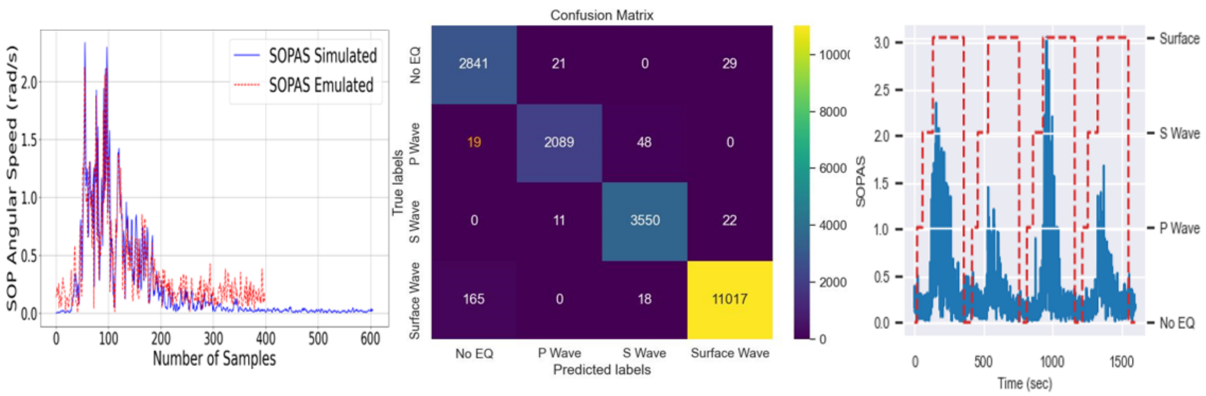

Fig. 2: One Example of Comparing B2B and Propagated B2B SOPASs through 38km of Fiber Cable (left), Confusion Matrix for Multi-Class Classification of Seismic Events Tested on Propagated Emulation (middle), and Fitting the ML Model to Detect Multiple Seismic Events Tested on Propagated Emulation(right).

4. Conclusion

This study demonstrates the effectiveness of a machine learning model in early earthquake detection by identifying the patterns of polarization changes, despite propagation challenges over a 38km of fiber cable deployed in Turin, Italy. The results highlight the successful integration of transfer learning, where a pre-trained model on simulated data is fine-tuned on an experimental dataset, showcasing the potential of using the entire optical network as a sensing grid for real-time earthquake early detection.

Acknowledgements

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