Experimental Earthquake Early Detection through Polarization Changes in Intelligent Optical Networks

Hasan Awad[1*], Stefano Straullu[2], Fehmida Usmani[1, 3], Emanuele Virgillito[1], Rudi Bratovich[4], Francesco Aquilino[2], Roberto Proietti[1], and Vittorio Curri[1]

[1]DET, Politecnico di Torino, Torino, Italy
[2]LINKS Foundation, Torino, Italy
[3]National University of Computer & Emerging Sciences, Pakistan
[4]SM-Optics, Cologno Monzese, Italy

ABSTRACT

In this paper, we replicate the dynamics of an earthquake in a laboratory experiment by employing an optical scrambler and a polarimeter. This experimental setup emulates the impact of a real earthquake-induced ground displacement values on the state of polarization of light propagating through an optical fiber, modeled using a Waveplate computer-based approach. A large dataset of polarization evolution was collected from the experiment to evaluate the performance of our pre-trained machine learning model in detecting the primary earthquake wave which precedes the destructive wave by tens of seconds. The objective is to perform a comparative analysis with our previous findings which were conducted using the same machine learning model, but applied to computer-based simulations of the Waveplate model. The results demonstrate that the model achieved over 95% of accuracy in both computer-based simulations and Laboratory-based experiment, validating the high accuracy and reliability of our system in early earthquake detection despite the inherent challenges of experimental errors.

Keywords: Fiber-Sensing, Polarization, Earthquakes, Terrestrial, Optical-Fiber-Networks, Machine-Learning

1. INTRODUCTION

Optical fibers, widely deployed around the globe, have shown great potential as distributed sensor arrays for detecting external events, particularly due to their sensitivity to environmental changes. By responding to these changes through expansion or contraction, optical fibers can capture valuable data about their surroundings, making them suitable for applications like structural health monitoring,[1] earthquake detection,[2] and environmental surveillance.[3] Among these applications, earthquake detection has gained significant attention, as it remains one of the most serious threats to humanity. This is especially due to P-wave, the primary earthquake wave, which precedes the destructive wave by tens of seconds and enable early detection, providing valuable time for early warnings to be issued before severe shaking occurs.[4] Distributed optical fiber sensors can detect the arrival of a P-wave using various techniques, one of which involves monitoring alterations in the State of Polarization (SoP) of light propagating through the fiber, allowing the detection of ground motion that is typically imperceptible to humans.[5] Thanks to the computer-based Waveplate model,[6] which facilitates the generation of large set of SoP evolution for a given earthquake.

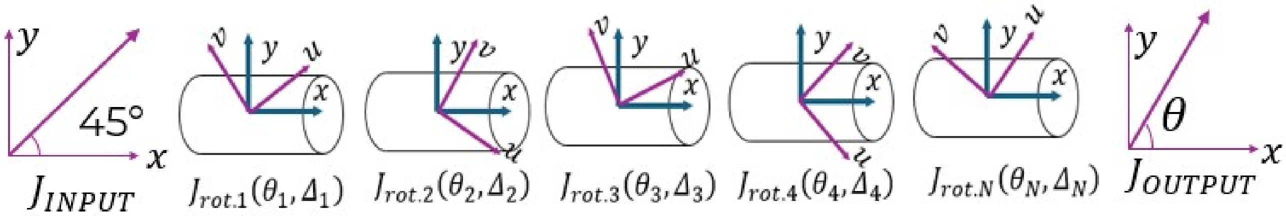

Figure 1. Waveplate Model

Further author information: Hasan Awad, PhD, hasan.awad@polito.it

This model divides the fiber into thousands of uniform internal birefringent segments referred as plates with randomly oriented polarization axes, where earthquake-induced strain is incorporated as phase shifts between the orthogonal polarization components as shown in Fig. 1, and the output SoP jones vector is characterized by:

$$J_{\text{out}} = \prod_{k=1}^{N} J_k(\theta_k, \Delta_k) \cdot J_{\text{in}}.$$

These plates account for both internal birefringence, caused by fiber construction imperfections, and external birefringence induced by external events. Ensuring a uniform internal behavior is crucial to isolate deviations caused by external perturbations. By assigning a unique set of angles to the plates in each simulation, the model captures diverse SoP evolution patterns for the same earthquake, enhancing the ability to analyze and detect seismic activity. Exploiting Machine Learning (ML) algorithms to this dataset enables the identification of the specific pattern of SoP change induced by different seismic waves associated with a particular earthquake, thus defining the arrival of a P-wave.[7] Building on this approach, we managed to exploit the entire optical fiber terrestrial network as a whole centralized smart sensing and epicenter localization grid. In,[8] an ML model was trained on data from seven real earthquakes that struck in the Modena region of Italy, with magnitudes ranging from 4 to 6. For an M4.3 earthquake test case, the system provided early warnings to different municipalities in the region, depending on their distance from the epicenter. This allowed a 21 seconds to 57 seconds time window to implement earthquake countermeasures and initiate rapid emergency plans. The model achieved 99% accuracy in detecting the P-wave, with a one-second of ML detection time. In comparison with other Distributed Fiber Optic Sensing (DFOS) mechanisms,[9,10] SoP sensing neither requires dedicated dark fibers nor demands expensive equipments to be added to the network. Instead, it leverages the existing traffic-carrying optical network, offering a cost-effective approach for large-scale environmental monitoring. In this paper, we replicate the dynamics of the same M4.3 earthquake previously tested on the ML model. Unlike previous studies that relied solely on computer-based simulations of the Waveplate model, we emulate the effects of earthquake-induced strain on the SoP of Light using a laser, an optical scrambler, and a polarimeter. Section II describes the controlled laboratory environment, Section III presents the ML model results on the experimental dataset compared to the computer-simulated one, and Section IV concludes the discussion.

2. EMULATING EARTHQUAKE DYNAMICS

On 23rd of May, 2012, an M4.3 earthquake struck in the Modena region of Italy according to the Italian National Institute of Geophysics and Volcanology (INGV)[11] as shown in Fig. 2.

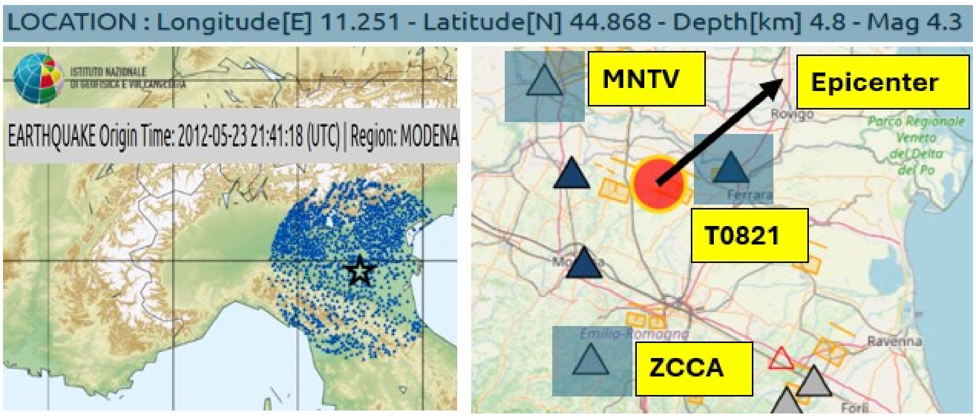

Figure 2. Epicenter Location and Seismic Stations for the M4.3 Earthquake in Modena Region

In previous studies we tested our ML model on three interconnected mesh networks, with a fiber cable in each network positioned within the earthquake coverage area and aligned with the geographical locations of seismic stations recording the event (T0821, MNTV and ZCCA), accounting for varying distances from the epicenter.[8] Exploiting the computer-based Waveplate model, and after coupling the earthquake-induced ground displacement values into strain along the fibers as phase shifts between the orthogonal components of polarization, we collected large sets of SoP alterations over these networks. The ML model was then evaluated for its ability to detect alterations associated with the P-wave, the primary earthquake wave, as well as the Surface-Wave, the destructive seismic wave. Building on this, we re-evaluate the model by testing it on emulated SoP data generated in a controlled laboratory environment that replicates the data collected from the ZCCA optical network. This emulation process shown in Fig. 3, involves using a tunable laser, operating at a wavelength of 1550 nm and an output power of 6 dbm to produce the optical signal. The optical signal then pass through an optical scrambler to replicate the polarization changes observed in the Waveplate simulation, which was derived from ground displacement values.

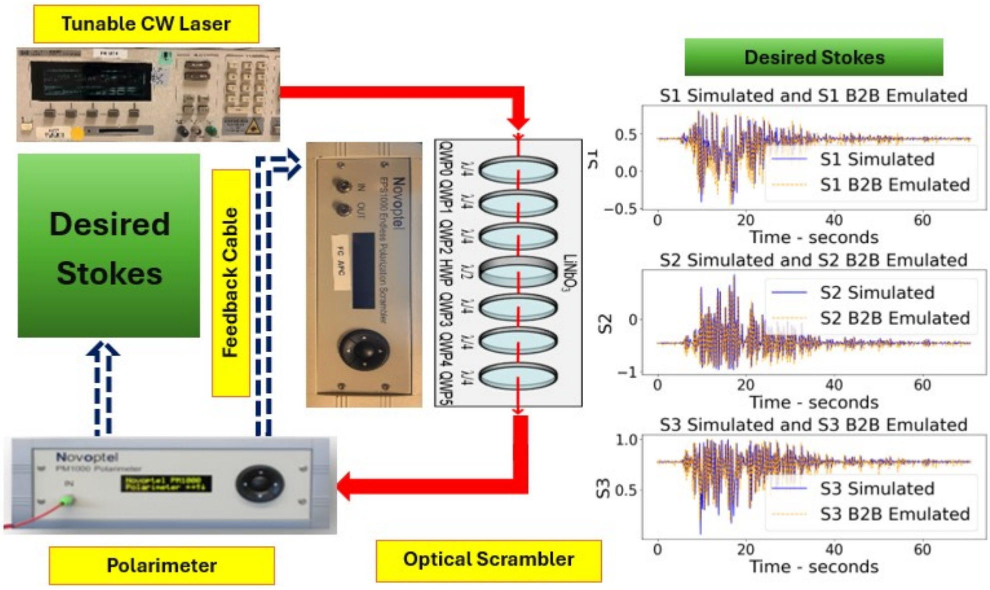

Figure 3. Laboratory Setup

In Fig. 3, the red arrows represent the optical signal path, while the dashed blue arrows indicate electrical connections, such as feedback or control signals. The scrambler replicates SoP dynamics by manipulating the polarization state of light passing through it using a series of adjustable waveplates with orientations dynamically controlled by applying specific voltages. These voltages are calibrated to align the output SoP with a target SoP at each time instance. A feedback loop, involving a polarimeter, measures the actual SoP and compares it to the target, iteratively adjusting the waveplate orientations using a minimization algorithm. This process ensures the accurate replication of the desired SoP evolution recorded over the ZCCA network, effectively mimicking earthquake dynamics. The comparison between the emulated and simulated signals, as shown on the right of Fig. 3, demonstrates the reliability and accuracy of the system in replicating these dynamics, with a close alignment observed in both evolutions. Minor deviations are attributed to experimental noise, but despite this error, the two signals still exhibit a strong correlation and alignment.

3. MACHINE LEARNING MODEL RESULTS AND COMPARISON

The ML pre-trained model employs a deep learning architecture combining both, a Long Short-Term Memory layers (LSTM)[12] and an Attention Mechanism.[13] We choose to calculate the State of Polarization Angular Speed (SOPAS) evolution rather than the full SoP.[14] This is because working with a single parameter evolving over time instead of three (S1, S2 and S3) reduce complexity and minimize computational time. The model was initially trained on SOPAS datasets to learn complex pattern of polarization alterations caused by different seismic waves (Primary Wave, Secondary Wave, and Surface Wave). Four LSTM layers are used to analyze the SOPAS inputs and return the full sequence of outputs to further process temporal dependencies, improve model's ability to define different 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. After leveraging the knowledge of previous training, we apply transfer learning and fine-tune the model on a smaller dataset, which is the one for ZCCA optical network, allowing the model to adapt to experimental conditions despite the inherent challenges of the corresponding noise. The fine-tuning was conducted over 10 epochs while preserving the knowledge gained from larger dataset to minimize the reliance on extensive labeled data. This study also demonstrates how transfer learning adapts to new data, transitioning from a computer-based approach to a laboratory-based environment.

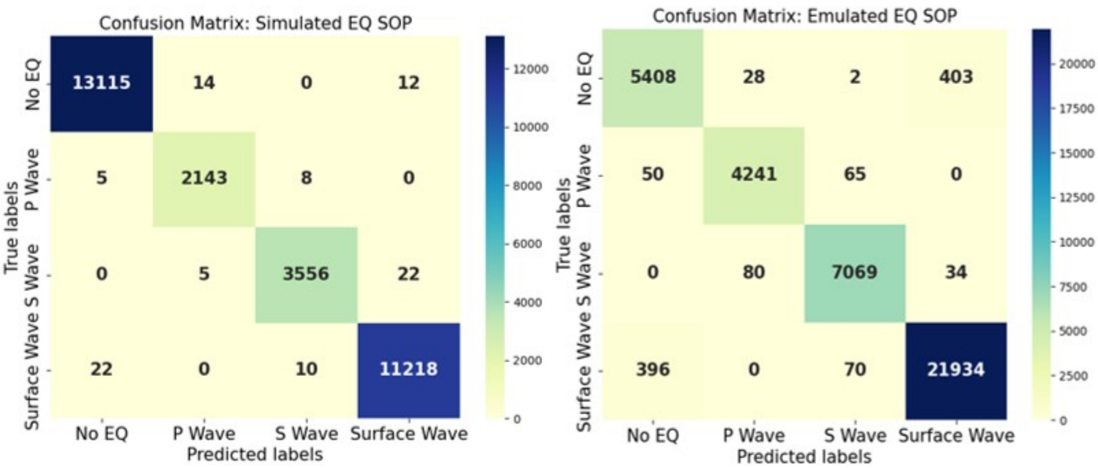

Figure 4. Confusion Matrices for Simulated and Emulated Data

The confusion matrices in Fig. 4 illustrate the model's high accuracy in detecting different seismic waves. For the simulated data, 2143 correct P-wave detections out of 2156, with 5 wrongly detected as "No Earthquake" and 8 wrongly detected as Secondary wave or "S-wave". In contrast, 4241 correct P-wave detections were achieved for the emulated data out of 4356. Similarly, for other wave detections. These results demonstrate 99% of accuracy rate in detecting different waves for the simulated dataset, while the model achieved 97% for the emulated data. Furthermore, the machine learning detection time remains consistent at one second for both datasets, ensuring real-time applicability of the approach.

4. CONCLUSION

This paper demonstrates the feasibility of using polarization sensing in intelligent optical networks for early earthquake detection. By replicating the dynamics of a real seismic event in a controlled laboratory environment and by leveraging a pre-trained machine learning algorithm, the system achieved high accuracy in detecting various seismic waves, particularly in identifying the arrival of the earthquake's Primary Wave, ensuring real-time applicability. Furthermore, the results highlight the adaptability of the transfer learning approach in transitioning from simulated to experimental conditions. Such advancements will pave the way for an in-field testing and large-scale deployment in seismic areas, offering critical time for emergency response and the implementation of earthquake countermeasures.

ACKNOWLEDGMENTS

The presented work was supported by the Italian National Recovery and Resilience Plan (NRRP) of NextGenerationEU, a partnership on "Telecommunications of the Future" (PE00000001—program "RESTART") and by the project FAAS funded by OpenFiber.

REFERENCES

[1] Wu, T., Liu, G., Fu, S., and Xing, F., "Recent progress of fiber-optic sensors for the structural health monitoring of civil infrastructure," *Journal of MDPI, Sensors* **20**, 4517 (2020).

[2] Awad, H., Usmani, F., Virgillito, E., Bratovich, R., Proietti, R., Straullu, S., Pastorelli, R., and Curri, V., "Seismic detection through state-of-polarization analysis in optical fiber networks," in [*Optical Fibers and Sensors for Medical Diagnostics, Treatment, and Environmental Applications XXIV*], Gannot, I. and Roodenko, K., eds., *Proc. SPIE* **12835**, 128350L (2024).

[3] Virgillito, E., Straullu, S., Aquilino, F., Bratovich, R., Awad, H., Proietti, R., D'Amico, A., Pastorelli, R., and Curri, V., "Detection, localization and emulation of environmental activities using sop monitoring of imdd optical data channels," in [*International Conference on Transparent Optical Networks*], *Proc. ICTON*, 1–4 (2023).

[4] Yamamoto, S. and Tomori, M., "Earthquake early warning system for railways and its performance,"," *Journal of Japan Society of Civil Engineers* **1**, 322–328 (2013).

[5] Usmani, F., Awad, H., Virgillito, E., Bratovich, R., Straullu, S., Aquilino, F., Proietti, R., Pastorelli, R., and Curri, V., "Earthquake early warning through terrestrial optical networks: a bi-gru attention model approach on sop data," in [*Optical Fiber Communication Conference*], *Proc. OFC*, Tu3J.2 (2024).

[6] Curti, F., Daino, B., Marchis, G. D., and Matera, F., "Statistical treatment of the evolution of the principal states of polarization in single-mode fibers,"," *Journal of Lightwave Technology* **8**, 1162–1166 (1990).

[7] Awad, H., Usmani, F., Virgillito, E., Bratovich, R., Proietti, R., Straullu, S., Pastorelli, R., and Curri, V., "A machine learning-driven smart optical network grid for earthquake early warning," in [*International Conference on Transparent Optical Networks*], *Proc. ICTON*, 1–6 (2024).

[8] Awad, H., Usmani, F., Virgillito, E., Bratovich, R., Proietti, R., Straullu, S., Aquilino, F., Pastorelli, R., and Curri, V., "Environmental surveillance through machine learning-empowered utilization of optical networks," *Journal of MDPI, Sensors* **24**, 3041 (2024).

[9] Soto, M. A. and Ramírez, J. A., "Earthquake monitoring using fibre-optic distributed acoustic sensing," in [*European Conference on Optical Communications Conference*], *Proc. ECOC*, 1441–1444 (2023).

[10] Marra, G., Fairweather, D. M., Kamalov, V., Gaynor, P., Cantono, M., Mulholland, S., Baptie, B., Castellanos, J. C., Vagenas, G., Gaudron, J.-P., Kronjäger, J., Hill, I. R., Schioppo, M., Edreira, I. B., Burrows, K. A., Clivati, C., Calonico, D., and Curtis, A., "Transforming subsea optical cables into a giant network of environmental sensors," in [*Optical Fiber Communication Conference*], *Proc. OFC*, M2C.1 (2023).

[11] INGV, "Italian National Institute of Geophysics and Volcanology." http://ismd.mi.ingv.it/ismd.php?tipo=lista. (Accessed: 20 April 2024).

[12] Hochreiter, S. and Schmidhuber, J., "Long short-term memory," *Journal of Neural Computation* **9**, 1735–1780 (1997).

[13] Jia, Y., "Attention mechanism in machine translation," *Journal of Physics: Conference Series* **1314**, 012186 (2019).

[14] Pellegrini, S., Rizzelli, G., Barla, M., and Gaudino, R., "Algorithm optimization for rockfalls alarm system based on fiber polarization sensing," *IEEE Photonics Journal* **15**, 1–9 (2023).