Machine Learning-Driven Earthquake Early Warning Using Optical Fiber Mesh Networks

# Machine Learning-Driven Earthquake Early Warning Using Optical Fiber Mesh Networks

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***Abstract*—We demonstrate interconnected meshed optical networks as sensing-localization grid for earthquake early detection. We integrate noisy polarization evolution data induced by seven earthquakes, into a Waveplate model to enhance a machine-learning algorithm that accurately detects primary waves, improves urban safety and mimic real case scenarios.**

***Keywords*—earthquakes, polarization, machine learning, early warning, optical network, waveplate model, sensing**

## I. Introduction

Earthquakes often precede variations in strain rates at which the Earth's crust either stretches or compresses [1]. These changes, primarily induced by the arrival of primary waves, tens of seconds before the destructive surface waves struck, serve as significant indicators for upcoming seismic events [2]. Buried underground, optical fibers experience alteration in both mechanical and optical properties. Therefore, we have witnessed a recent emergence of Distributed Fiber Optic Sensors. Unlike Distributed Acoustic Sensing [3] and interferometric techniques [4], our polarization sensing-based approach [5] requires no dedicated dark fibers or adding expensive equipment to the network. State-of-Polarization (SOP) based techniques monitor polarization changes of the modulated light propagating through traffic-carrying optical fibers [6]. These changes could be induced by anthropic activities [7], or environmental events, such as earthquakes [8]. In [5], and as shown in Fig. 1, we utilized 3 sensing fibers (positioned at exact geographical coordinates as three seismic stations) in 3 interconnected mesh optical networks in T0821 Area ($\sim$ 20 km far from the epicenter), MNTV ($\sim$ 40 km far) and ZCCA ($\sim$ 60 km far) in the Modena region of Italy focusing on the whole network as a sensing grid. By triangulating over these areas, we managed to localize the epicenter coordinates and determine the epicenter-fibers distance to generate early warning to municipalities close to the epicenter and progress to those further away. This approach was developed to detect primary wave's arrival, leveraging a Machine Learning (ML) model that was trained on polarization evolution data induced by recorded real ground displacement data from seven local earthquakes, magnitudes ranging from 4 to 6, on different seismic stations. In this manuscript, we extend the use of our model to closely describe real case scenarios by integrating noise level into the extracted polarization evolution data and enhance ML model's resilience and generalization capability, presented in [5]. This approach is crucial because in real case scenarios various factors, not just earthquakes, affect the polarization. In Section II, we describe the methodology and present the case scenario. Section III demonstrates ML model testing results. Lastly, Section IV concludes the discussion.

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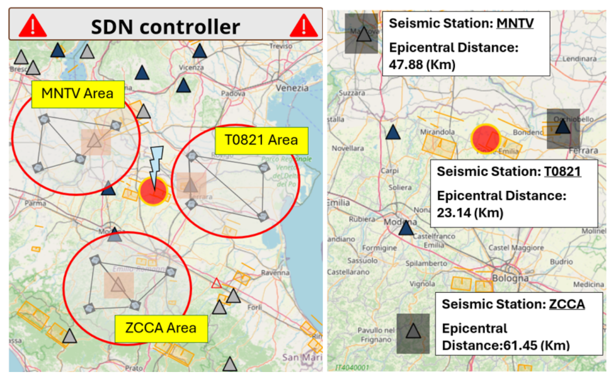


Fig. 1. Interconnected Mesh Optical Sensing-Localization Network

## II. Methodology and Case Scenario

### A. State of Polarization Evolution Data Extraction

The purpose is to segment the fiber into small sections (plates) to define the effect of internal birefringence, stemming from fiber's construction imperfections, on the change of light's SOP. This approach is known as the Waveplate model [9]. We extended the use of this model to convert earthquake displacement values recorded by seismic stations at INGV [10] to strain-time matrices along the fiber [11]. Large set of SOP evolution is extracted from Waveplate model simulations for each earthquake strain values, due to the fact that in each simulation the plates are inherently assigned to random orientations. To minimize computational time, we calculate from each SOP file the State of Polarization Angular Speed (SOPAS) [12]. Additive Gaussian noise is added to the resulting SOPAS data, which is then utilized to train an ML algorithm capable of detecting primary wave's arrival for each seismic event. The trained ML algorithm is then tested on an earthquake among the same range of magnitudes (M4.3), highlighting the use of the whole interconnected optical networks as a sensing grid.

### B. Case Scenario

The main idea of our approach is to add Gaussian noise to the original SOPAS values. We computed signals' standard deviations and used the desired signal-to-noise-ratio (SNR) of 0.1 to calculate the noise level. Subsequently, this noise was integrated over all data to generate a more reliable dataset that mimics the variability present in real-world case scenarios. The ML model utilized combines the Temporal Convolution Network (TCN) [13], Long Short - Term Memory (LSTM) [14] and attension mechanism. Referring to Fig. 2, the model


Fig. 2. Training and Validation Loss of the Machine Learning Model

training and validation accuracy curves increase rapidly and stabilize around 95%, indicating that the model learns quickly and generalizes well. As for the model loss, both curves stabilize near zero, indicating effective learning and minimal over-fitting. Fig. 3 shows detection precision for our model.

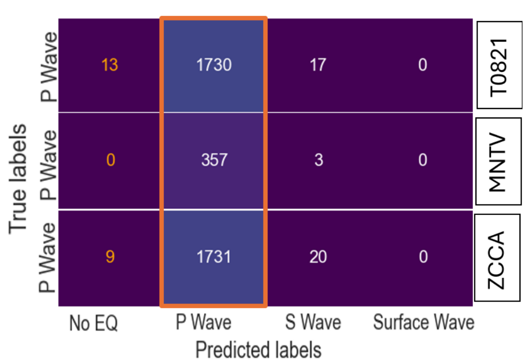


Fig. 3. Confusion Matrix for Three Stations/Fibers

For instance, for T0281/Fiber, 1730 correct detection out of 1760. The model shows 98% overall accuracy for primary wave detection and one second detection time. This indicates that refining our model against noise level comparing to what we present in [5], leads to the same results, where the optical network controller overseeing all interconnected networks can still inform all municipalities about an upcoming seismic event after the third confirmation from ZCCA fiber and is able to detect primary waves in noisy environment. Consequently, and similarly to [5], the T0821 area is the first to be notified with a 21 s time lag for an emergency response before the surface wave strikes, followed by the MNTV area with a 35 s time lag and then the ZCCA area with a 57 s time lag.

## III. Conclusion

We investigated the use of interconnected fiber optic mesh networks as a sensing-localization grid for accurate ML-based earthquake early warning approach in a noisy environment. Data were extrapolated from real earthquakes of different magnitudes recorded by INGV in the region of Modena, Italy.

## Acknowledgment


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