A Machine Learning-Driven Smart Optical Network Grid for Earthquake Early Warning

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ABSTRACT

Optical fiber networks, commonly recognized for their role in data transmission, have the potential to be extended beyond their conventional use. These networks could serve as wide distributed arrays of sensors for earthquakes early detection by monitoring and identifying specific evolution patterns of the light's state of polarization (SOP) caused by the strain induced by external perturbations on fiber cables. We propose a centralized smart grid system that take advantage of the existing terrestrial network infrastructure, offering an efficient solution for earthquake early warnings and early emergency responses by detecting earthquake primary waves (P-waves). Our focus is on monitoring changes in light's polarization due to the strain induced by primary waves' arrivals, and subsequently use this data to refine and evaluate a machine learning model to interpret and detect these changes. This paper presents a novel neural network model based on Temporal Convolutional Network employed on our smart grid sensing approach. Tested on real earthquake data, our method achieves accurate detection of primary waves with 98% of accuracy rate.

Keywords: Earthquakes, Early-Warnings, State-of-Polarization, Machine-Learning, Waveplate-Model

1. INTRODUCTION

In the last years, telecommunication optical networks have witnessed an enormous acceleration in the amount of transported data and geographical coverage, effectively becoming one of the most strategic capillary and pervasive infrastructure with tens of thousand of kilometers of deployed optical fibers. At the same time, these networks are evolving towards autonomous and software-defined commodities able to expose differentiated networks services besides the plain data transmission. Recently, much attention is being posed to the use of optical networks for the monitoring of the environmental conditions and the development of disaster early warning system, especially with respect to earthquakes. While there is a large consensus in the scientific community on the many challenges associated with earthquake prediction [1], it is crucial to approach the problem differently by finding innovative methods for widely distributed early detection systems capable to quickly identify and localize the event in order to activate different mitigation strategies and minimize the damages for the critical infrastructures. In this context, the utilization of optical fiber networks presents a promising new direction. Change in strain rates due to seismic events stretches or compresses the earth's crust, and such strain is coupled to optical fiber cables laying or buried underground. In response to this, the mechanical and optical properties of an optical fiber, as well as the physical properties of the light wave propagating inside it, change due to applied mechanical stresses and external disturbances. Hence, distributed fiber optics sensing (DFOS) has drawn much attention in the seismology field as it enables *distributed* observations in space of the characteristics of a seismic wave [2]. DFOS can detect the Primary waves (P-Wave) of an earthquake that propagate through the earth's interior and precede the destructive Surface waves (S-Wave) that propagate along the Earth's surface. Surface waves carry the greatest amount of energy and are usually the primary cause of destruction [3]. Detecting P-waves that precede earthquake's destructive waves allows prompt initiation of emergency plans and early warning systems. DFOS offer the possibility of measuring a slow varying environmental variable at any location along the fiber length with a given sharp spatial resolution [4]. This approach has been developed in the last decade to monitor dynamic strain variations using optical fibers. DFOS leverages natural scattering processes in optical fiber cables such as Rayleigh Scattering to enable Distributed Acoustic Sensing (DAS) systems, that detect disturbances from the back-scattered light induced by external perturbations. These technologies open the perspective of using the optical network infrastructures deployed for telecommunications as a wide distributed network of sensors for earthquake early detection, as discussed also in several recent publications. One drawback of DAS is related to its effective range under 100 km [4], [5]. Moreover, DAS devices are expensive and cannot be implemented easily on typical optical data fiber networks links due to the presence of optical amplifiers and potential interference with data signals, thus preventing its wide diffusion. To overcome these limitations and to allow integration of sensing services in the optical data network infrastructure, sensing techniques based on monitoring of other light's physical quantities have been proposed. One relies on the optical signal's phase monitoring: these are mainly interferometric techniques leveraging ultra-stable laser cavities to measure femtosecond-level of delay experienced by light traveling in the fiber at micrometer scale over several thousands of kilometers [6]. Yet, the implementation of this interferometric technique demand expensive and specialized ultrastable lasers [6], and is only capable to detect longitudinal strain on the optical fiber. Another technique relies on the monitoring of signal's state of polarization (SOP) variation caused by strain induced birefringence. SOP based sensing is sensitive to strain that modifies the fiber's cylindrical symmetry, it does not require bidirectional signal propagation, and can be implemented using intensity modulated data channels which are still widespread in optical networks. This technique is cost effective, addressing the issue of effective range observed in DAS, and requires a minimum number of add-on components, making it attractive for integration in existing optical networks [7]. In [8], Z.Zhan and his team presented a similar approach based on state of polarization monitoring on transoceanic cables. Our approach propose to exploit the existing optical fiber terrestrial network as a whole centralized smart sensing grid enhanced by machine learning to analyze and interpret the alteration of light's polarization along the optical cables due to a seismic event. While several sensing techniques have been studied in the last years, more work need to be done on the post-processing of the raw monitored data in order to extract information and recognize an incoming earthquake, especially when employing SOP sensing technique in a terrestrial and metropolitan scenario, where many sources of additional polarization noise are present, like a simple car passage, as illustrated in [9]. While Machine learning (ML) based techniques are perfect candidates to cope with the detection problem, large dataset are required to train and test them reliably. In [10], we have proposed a simulative approach capable to generate a synthetic dataset providing a collection of SOP evolutions caused by the strain of a predetermined earthquake recorded by a DAS interrogator. In this work, we employ the same synthetic SOP evolutions' data generation framework to train a machine learning model aimed at detecting the earthquakes P-wave as further step in the feasibility demonstration of an early warning system based on SOP sensing. In Section 2 we briefly recall the SOP sensing technique and its emulation in our synthetic SOP data generation tool, along with an overview of our previous related work. Section 3, discusses the optical network smart grid approach. The case scenario is presented in Section 4, followed by results and discussions in Section 5, and the conclusion in Section 6.

2. State of Polarization Sensing Methodology

As demonstrated in [11], it is possible to gather information about mechanical stresses induced by observing the SOP evolution of a signal traveling in a fiber. In [12], we have experimentally tested the polarization sensing approach on a deployed fiber ring in the city of Turin, Italy, using commercial Intensity Modulated-Direct Detected transceivers and polarimeters as state of polarization sensing devices, in order to detect and localize passage of cars from observing state of polarization variations footprint. The experimental results showed the feasibility of event's detection and localization with less than 100 meters of accuracy, although such remarkable accuracy may be relaxed in realistic application scenarios. In order to simulate a possible SOP evolution corresponding to a certain strain applied to an optical fiber, we have developed a simulation framework which implements the well-known waveplate model [13]. Each fiber is subdivided into waveplates, each of length dz, depending on the fiber correlation length, to ensure a spatially uniform internal perturbed medium in each section and properties like the refractive index assumed to be constant. This is crucial, as due to construction imperfection, the fiber internal medium is birefringent and it is significant to isolate the internal behaviour from the external induced one in order to better study SOP alteration's cause. Moreover, each waveplate has its own principal birefringence axis whose orientation is random and uncorrelated with respect to the previous waveplate. This adds more complexity to analyze SOP changes induced by external effects. As a result, we propose to accumulate a dataset of SOP evolutions carrying out a Montecarlo simulation over different random birefringence orientations realizations. The purpose is to train a machine learning model on all this set of data, in order to detect and interpret the pattern of polarization change upon Primary earthquake waves arrival. In previous work, we generated synthetically ground motion displacement waves using SYNGINE [14], to emulate displacement waves for a real 4.9 magnitude earthquake that struck in Marradi Region, in central italy. By leveraging our waveplate model and a Bi-directional GRU machine learning algorithm that was trained and tested on two fiber cables acting as substitutes of two seismic stations located in distinct cities, we managed to obtain 97% of accuracy in detecting earthquake Primary waves [15]. Additionally, in [16], we managed to extract the real ground motion data for the same M4.9 earthquake in Marradi from the National Institute of Geophysics and Volcanology in Italy [17], instead of generating it synthetically, we apply the same approach, and detect the arrival of Primary waves with the same accuracy rate. In this manuscript, and to further investigate this technique for earthquake early detection in terrestrial areas, we leverage the same real earthquake data, but instead, focusing on the whole network as a sensing grid. Our objective is to utilize the existence of six fiber cables acting as six seismic stations, train a machine learning model on four nodes, and test it on two nodes, which in turn refine our model early detection capabilities.

3. Smart Grid Sensing Approach

Optical networks are evolving into dynamically re-configurable, and autonomous systems to address the rapidly changing patterns of traffic. These networks are managed by a centralized optical network controller (ONC), which interacts with one another and interacts with network elements (NEs) by means of Application Programming Interfaces (API) to facilitate network management and control. We propose to expand the existing network into streaming telemetry paradigm to integrate earthquake early detection services as depicted in Fig. 1.

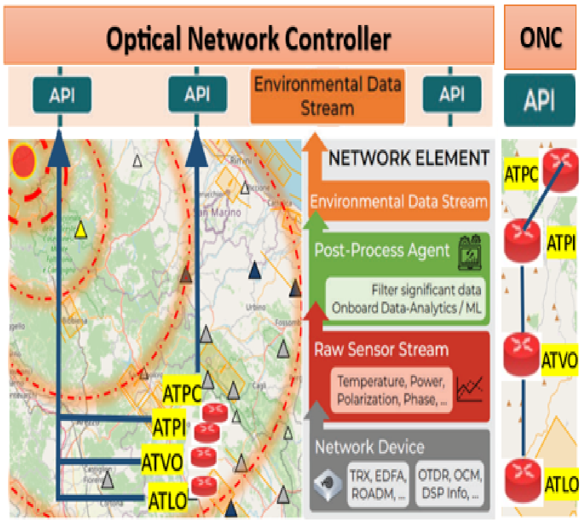

Figure 1: Sensing Network Architecture

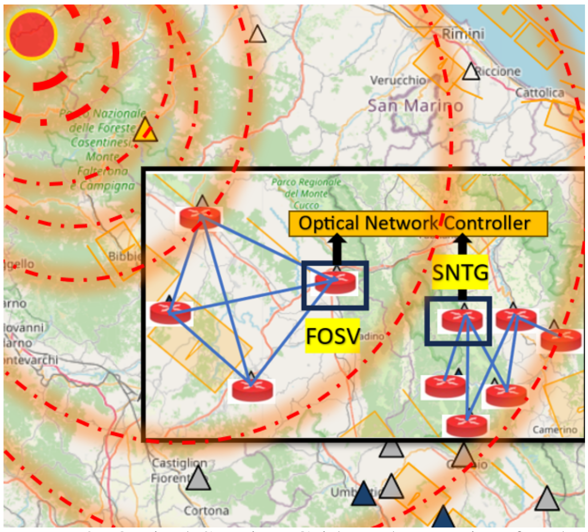

Figure 2: Optical Sensing Grid Under Testing for the same Marradi Earthquake

On September 18, 2023, a M4.9 earthquake struck the Marradi area in central Italy. This seismic event was recorded by the Italian National Institute of Geophysics and Volcanalogy (INGV) [17]. According to the Central Italian Apennines (CIA) velocity model, the seismic wave velocity was measured at 7.10 km/s. This velocity is determined based on the characteristics of the earth's interior in the specific region [18]. Indeed, external perturbations affect the state of polarization of propagating optical pulse along the fiber. Thus, these changes could be used for environmental sensing [9]. Although devices like coherent transceivers include information about state of polarization, yet this information is often not available due to vendor lock. However, more cost-effective Intensity Modulated-Direct Detected (IM-DD) transceivers are still widely used in metro and access networks. These networks either operate at lower data rates or function as Optical Supervisory Channels (OSCs). IM-DD signals are polarized, effectively allowing the detection of OSC state of polarization (SOP) changes caused by external stresses. This is achieved by extracting small amount of power to supply SOP monitoring device like a basic Polarimeter or simpler Polarization Beam Splitter (PBS)-based solutions [7]. The streaming telemetry paradigm involves continuous data transmission from network elements (NEs) to the optical network controller (ONC). As shown in Fig. 1, a post processing agent should be pre-trained on earthquakes with same magnitude in order to detect the arrival of Primary waves. The post processing agent is a machine learning algorithm that can be implemented within the NEs, to provide the latter detection based on SOP variation, and leverage NEs' edge-computing capabilities. Consequently, we assume to replace four seismic stations (ATPC, ATPI, ATVO, and ATLO) by using four fiber cables of 10 kilometers each. We extract the real ground motion recorded on these stations by exploiting INGV data, and convert ground displacement to strain values coupling the fiber using the aforementioned Waveplate model. This conversion was made under the iDAS conventional conversion presented in [19], where each 116 nanometers of displacement corresponds to 11.6 nano-strain. We run 100 simulations for each fiber, where each simulation corresponds to different SOP evolution over 300 seconds, due to the fact that each evolution has different set of orientation plates angles. The main objective is to train the machine learning on four nodes, in order to test and detect the Primary wave arrival on two other nodes. Different fibers/stations have different Primary waves' arrival times due to the varying distance from the epicenter, which is the full red circle on the up-left corner of the map shown in Fig. 1. The difference in time between Primary waves and the arrival of Surface waves for all fibers is 10 seconds. From a general perspective, by adding this time difference to the varying propagation time of the seismic wave to reach each fiber, we can generate early anomaly warnings. The state of polarization at each discrete time instant K is defined by the normalized stokes vector denoted as $\mathbf{S}_k$, with components $(S1[k], S2[k], S3[k])$. For less complexity purposes, instead of training and testing the machine learning model on data set where each file is defined by three parameters, we propose to calculate for each state of polarization evolution file, the state of polarization angular speed (SOPAS) proposed in [20], which is given by:

$$\omega[k] = \arccos\left(\frac{(\mathbf{S}_k \cdot \mathbf{S}_{k-1})}{\|\mathbf{S}_k\|\|\mathbf{S}_{k-1}\|}\right) \cdot \frac{1}{T_s} \tag{1}$$

The SOPAS is denoted by $\omega[k]$, and the sampling period by T_s, while $(\mathbf{S}_k, \mathbf{S}_{k-1})$ is the dot product between the Stokes vectors at time k and at time $k-1$. This computation is analogous to the discrete-time derivative of an angle $\omega[k]$. SOPAS hold the same seismic waves arrivals information shown in the stokes parameter for all fibers/stations and for all simulation runs.

4. Case Scenario

For ML testing purposes, and referring to the seismic data from the Italian National Institute of Geophysics and Volcanalogy (INGV) mentioned earlier, we choose to extract two seismic stations data located in two different municipalities with distinct distances from the epicenter. The first seismic station (FOSV) is located 126.9 km away from the epicenter in the municipality of Fossato di Vico, while SNTG in Esanatoglia municipality, located at 140.7 km distance from the epicenter. The reason we choose two sensing points is to determine the time available for each municipality to implement earthquake countermeasures, considering the varying distances of the two cities from the epicenter, which result in different Primary waves arrival time. An illustration of the network under testing is depicted in Fig. 2

5. Results and Discussion

In [15], the ML model we developed was trained and tested on two sensing fibers against synthetic seismic data to early detect Primary waves within one second. In [16], the model we developed was trained and tested on two sensing fibers against real seismic data, early detecting the primary waves in one second as well.
In this work, instead, we adopt a more comprehensive approach by expanding the scope to focus on the whole network as a sensing grid, where we train the machine learning model on four sensing fibers (substituting four seismic stations - ATPC, ATPI, ATVO, ATLO) and tested on two (substituting two seismic stations - FOSV, SNTG), employing the same real seismic data used in [16].

5.1 Proposed Model Architecture

In this study we introduce a novel neural network architecture based on temporal convolutional network (TCN) [21]. This proposed model is designed to capture complex time-related patterns in earthquake data.
The TCN layer characterized by a convolutional operation that offers an efficient method for capturing dependencies in earthquake data. Additionally, an attention mechanism is employed to enhance the model's ability to concentrate on key information in these sequences. The attention mechanism leverage a combination of dense layers to calculate attention weights and prioritize different parts of the input. The post attention Long Short-Term Memory (LSTM) cell processes the vector derived from the attention mechanism contributing to the final output layer that facilitate multi-class classification for No Earthquake, Body Waves (Primary and Secondary waves), and Surface waves[22]. Our focus is on detecting Primary waves as it precede the Secondary waves as well as the destructive Surface waves.

5.2 Model Training

The training of the model involves 500 epochs utilizing a categorical cross-entropy loss function. Adam optimizer was utilized for optimization, employing a learning rate of 0.0001. In addition, to avoid over-fitting, an early stopping was implemented based on training validation loss. The model was able to train and generalize based on the gradual decrease of the training and validation loss curves. Significantly, the training loss consistently decrease in the training period to reach a minimum. In parallel, the validation loss showed a similar behaviour reflecting the model's proficiency in adapting and generalizing to unseen data. The model efficiently capture the underlying patterns of data with no over-fitting, as the validation loss curve reach a minimum and remain stable.

5.3 Model Test

To further evaluate the performance of our model, we extracted the confusion matrix for all tested data on both nodes (FOSV and SNTG fiber substitutes), to visualize the performance of events classification and detection (No Earthquake, Primary waves, Secondary waves, and Surface waves). The confusion matrix show the correct and incorrect detections made by the model for each class. Fig. 3, represents the confusion matrix for the fiber substituting FOSV seismic station, where the matrix rows indicate the true label and the columns represent the

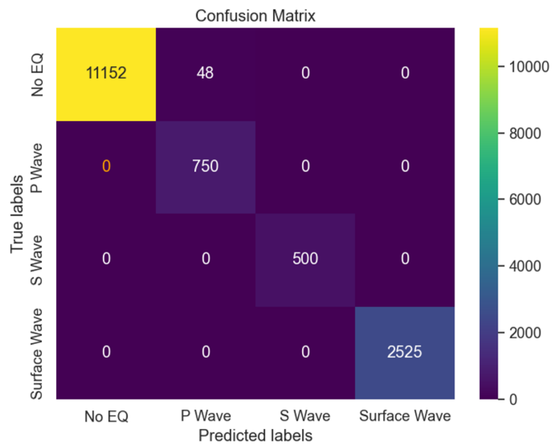

Figure 3: FOSV Fiber Substitute Confusion Matrix

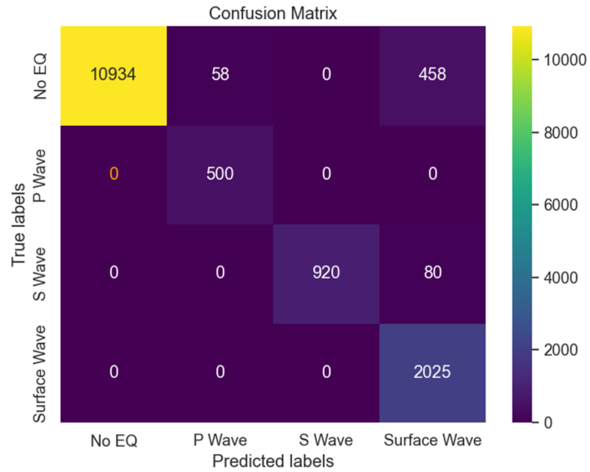

Figure 4: SNTG Fiber Substitute Confusion Matrix

detected labels. For instance for FOSV substitute, and for No Earthquake class, 11152 correct detections and 48 detected wrong as Primary waves. For Primary, Secondary, and Surface waves, 100% correct detections was made. Similarly with the same concept, for the fiber substituting SNTG seismic station in Fig. 4.
The assessment of model performance based on the confusion matrix shows 98% of an overall accuracy in detecting multiple classes of seismic event, which is considered a promising performance. With such precise detection, the model effectively captured the invariant feature characteristics of Primary waves. Such proficiency in detection lays a solid foundation in seismic waves analysis.
To further investigate the model performance in testing, we show a data sample, three SOPAS plots in order to highlight the time needed for the model to detect seismic waves, particularly Primary waves.

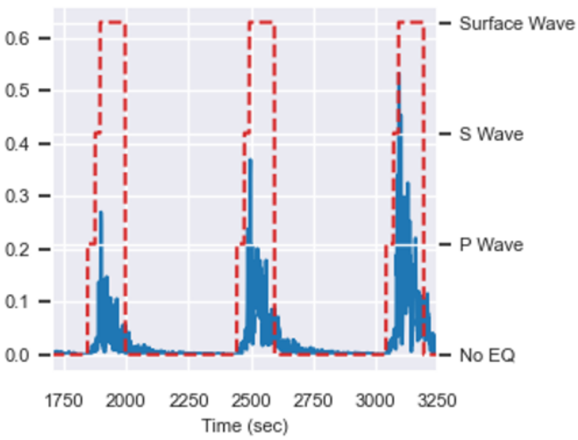

Figure 5: Machine Learning Detection for FOSV SOPAS

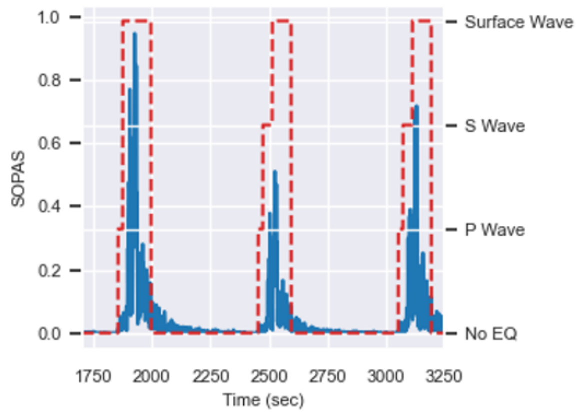

Figure 6: Machine Learning Detection for SNTG SOPAS

We pick up three samples for both fibers substituting the two seismic stations, where Fig. 5 corresponds to the FOSV fiber substitute and Fig. 6 corresponds to the SNTG fiber substitute. The proposed model show ability to detect Primary waves in almost one second. Therefore, as mentioned earlier FOSV or the municipality of Fossato di Vico is far from the epicenter 126.9 km, while SNTG or the municipality of Esanatoglia is 140,7 km far. Accounting to the seismic wave velocity which is 7,10 km/s according to the CIA model, the Marradi earthquake needs around 18 seconds to reach Fossato di Vico and around 20 seconds to reach Esanatoglia, $\left(v = \frac{d}{t}\right)$. After prior acknowledgment for the 10 seconds of difference between the arrival of Primary waves and Surfaces waves presented previously in this manuscript, Fossato di Vico has 27 seconds (18+10)-1 to take earthquake counter measures and initiate early warnings, while Esanatoglia has 29 seconds (20+10)-1. Thus, once the earthquake is detected by a sensing point in Marradi through the same machine learning approach, the municipality of Marradi will have 9 seconds for early warnings and can inform nearby municipalities by means of interconnected ONCs about the time needed for each municipality to generate alerts and initiate emergency plans accounting to the distance of each municipality from the epicenter. Thanks to the centralized smart-grid sensing approach. Having around 30 seconds warning prior to an earthquake can be crucial to minimize damages.

6. Conclusion

In this work we have proposed an SOP-based fiber sensing approach as a viable opportunity to exploit the vast optical data networks infrastructure for environmental sensing purposes. Using our waveplate-model based simulative framework, we have been able to obtain realistic evolution of the SOP change caused by a seismic wave, which represents a precious robust framework for future development of ML-based detection tools in early warning systems. WE have finally showed a realistic use case application, where we leverage real earthquake induced fiber strains, and we were able to estimate the available time for early warning alerts. For future work, we intend to exploit the same sensing grid approach to early detect different earthquakes with same magnitudes but different depth.

Acknowledgment

The presented work has been supported by the Italian National Recovery and Resilience Plan (NRRP) of NextGenerationEU, partnership on "Telecommunications of the Future" (PE00000001 - program "RESTART")

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