Real-time Intrusion Detection and Impulsive Acoustic Event Classification with Fiber Optic Sensing and Deep Learning Technologies over Telecom Networks

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Abstract *We review various use cases of distributed-fiber-optic-sensing and machine-learning technologies that offer advantages to telecom fiber networks on existing fiber infrastructures. By leveraging an edge-AI platform, perimeter intrusion detection and impulsive acoustic event classification can be performed locally on-the-fly, ensuring real-time detection with low latency.* ©2023 The Author(s)

Introduction

Distributed fiber optic sensing (DFOS) technology, which utilizes the fundamental sensing capabilities of optical fiber, has been applied in diverse applications, such as earthquake detection and monitoring [1], pipeline leakage detection [2], structure change monitoring [3], road traffic monitoring [4]. In recent years, there has been growing interest in applying fiber sensing technology to the telecom area, given the vast fiber infrastructures that telecom carriers have built over the past 30 years to support Internet traffic growth, particularly in preparation for 5G and beyond networks. While transmission fibers were originally intended solely for data transmission, they are now being explored as potential sensing media [5 – 7].

Operational telecom fiber networks offer significant potential for optical sensing applications. In turn, the sensing technology can be used to detect threats to the fiber infrastructure and contribute to community safety. In this paper, we reviewed field trial results utilizing fiber optic sensing and deep learning technologies for perimeter intrusion detection to safeguard the infrastructure and impulsive acoustic event detection to identify gunshot events for community safety.

Principle of DFOS

Figure 1 illustrates the key element of distributed fiber optic sensing: measuring nonlinear backscattering signals generated along the fiber route, including Rayleigh, Brillion and Raman [8]. Our study used a distributed acoustic sensing (DAS) system, based on Rayleigh optical time-domain reflectometer (OTDR) detection [7], which measures changes in intensity of Rayleigh scattering through interferometric phase beating. With coherent detection, the DAS recovers full polarization and phase information of backscattering signals. The system used a 1550-nm laser, sampling rate of 125 MHz, short optical pulses, and on-chip fast processing, achieving an equivalent sensor resolution as small as 1 meter.

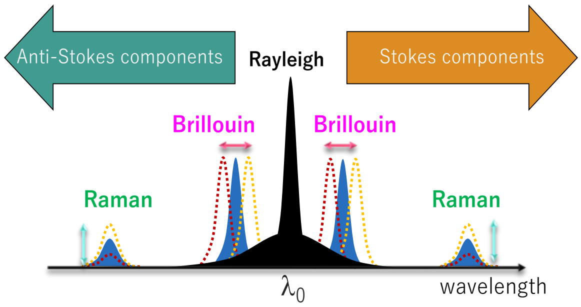

Fig. 1: Schematic of backscattering signals.

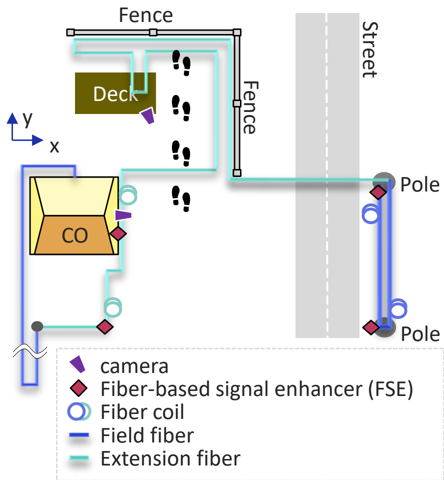

Fig. 2: Experimental Setup.

Experimental Setup

Figure 2 presents the trial setup which includes a DAS in the central office (CO), 38-km field fiber, and extension fiber outside the CO to protect the facility. The extension fiber is comprised of three sections of cable: buried underground, attached to the fence, and hanging on poles with coils. The CO acts as a sensing backbone, utilizing existing fiber for environmental monitoring such as road traffic, and is then cascaded to extension fiber for new sensing branches for applications such as intrusion detection using buried cables and impulsive acoustic event detection through aerial cables. Fiber coils and fiber-based signal

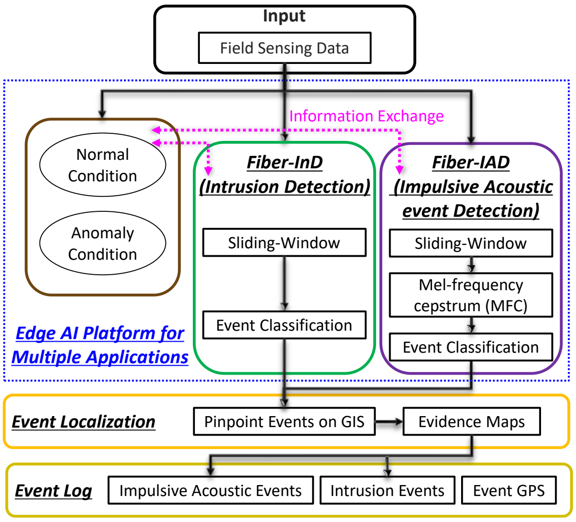

Fig. 3: Flow chart of the edge AI platform for simultaneous multipurpose sensing.

enhancers (FSEs) are simply integrated into the testbed, and event localization results are fused with video analytics to trace the subject associated with the event in space and time.

Results

In the study, fiber sensing and AI techniques are combined to provide data-driven solutions for various applications. Fig. 3 illustrates our multiple-in-one AI platform, which is hosted on a new architecture designed to run the pipelined computations locally. The platform incorporates multiple modules, making it more data-efficient and adaptable to dynamic environments. The platform can be trained end-to-end and provides results in real-time, enabling timely action. After receiving the sensing data, the engine filters out signals in normal conditions, such as road traffic trajectories, before feeding the data into the Fiber-InD (intrusion detection) and Fiber-IAD (impulsive acoustic event detection) modules.

Fiber-InD module, based on convolutional neural network (ConvNet), is proposed to classify events, such as human walking, running, and digging, with outputs that include event type and auxiliary information such as the location, time stamp, direction along the cable, and the class probability. Additionally, this module can be expanded with more intrusion events such as fence shaking, climbing, and cutting, and distinguish animal related events. During the trial, three types of actions were observed near buried cables: digging, driving, and human walking. A total number of 65,516 image patches are randomly sampled from the recorded data across different days, using 70% of data for training and 30% for testing. Each image patch has a size of 50×100, equivalent to 30 seconds of time duration and 160 meters in location. We

Class	Precision	Recall	F1-Score	Support
Digging	0.97	0.73	0.84	1347
Driving	1.00	0.98	0.99	11531
Walking	0.92	0.99	0.96	6778
Overall			0.97	19656

Table. 1: Intrusion detection classification results.

	Digging	Driving	Walking
Digging	986	0	361
Driving	8	11329	194
Walking	19	15	6744

Table. 2: Intrusion detection confusion matrix.

evaluated the proposed model's classification performance using precision, recall, and F1-score, the result is shown in Table 1. The confusion matrix between the three classes is shown in Table 2. Computationally, the inference time of the proposed model takes 0.528 seconds for a 20 km route on a laptop with NVIDIA RTX2080 Max Q GPU.

Additionally, a multimodal impulsive acoustic event detection system was developed using aerial coils, buried fiber, FSEs, and cameras. This system is capable of detecting and localizing impulsive event via DAS where it received the vibration patterns excited from the source and tracking the source of the sound through video analytics. The cameras were triggered by DAS to pinpoint the person at the sound location as the potential threat with an alarming boundary box in its visual recording. The cameras used in the system were a regular camera (Camera 1) and a fisheye camera (Camera 2), both of which were placed at different angles to cover a wide area. A ConvNet based object detection model was trained to identify and track the location of a person detected by the cameras. The model used ResNet50 as the backbone and employed the cascade Region-based ConvNet detector with a shared region proposal network across datasets. The subject can be therefore identified and tracked by associating the location coordinates of the detected sound with the coordinates of the detected persons' boundary box using an intersection over union operation. As shown in Fig. 5 (a) and (b), the subject was detected and tracked with a red boundary box in both cameras while pedestrians and vehicles are marked in green and blue boundary boxes. Additionally, the impulsive sound location was also visualized as the augmented heatmap through TDoA on a GIS. After that (Fig. 5(b)), the suspect invaded the protected area, which was in the camera's blind zones, as shown in Fig. 5(c). However, the buried optical fiber can be clearly detecting the suspect's footsteps and track his movement even in blind

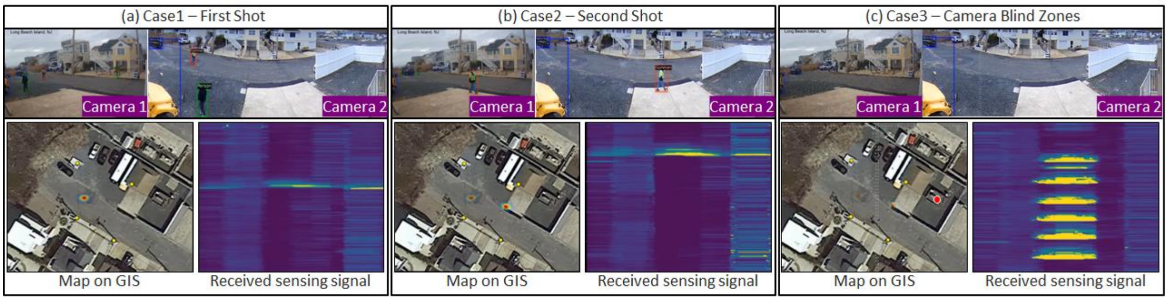

Fig. 5: Sensing fusion field results by integrating video and fiber sensing technologies to locate the subject.

zones of cameras. The system demonstrated the effectiveness of impulsive acoustic detection and tracing, particularly in cases where single-modality detection is insufficient.

One of the major challenges with impulsive acoustic event detection systems is false alarms. To address this issue, Fiber-IAD (shown in Fig. 3) was proposed, and a classifier was trained to distinguish multiple impulsive acoustic events based on the short-term power spectrum representation of the vibrations captured by the DAS. The data processing pipeline for this classification task includes temporal sliding-window analysis, computation of Mel-frequency cepstral coefficients (MFCCs), and ConvNet inference. It should be noted that the storage of MFCC data samples does not raise any privacy concerns, as MFCCs are not audible to humans. The results of confusion matrix are shown in Fig. 6 (a) and (b), different fireworks such as crackers, cannons, fountain cannons, and high-altitude fireworks were tested on FSE and fiber coil. Other safety-related sound events, such as car alarms, starter guns, and door slams, were also studied. By using the time-frequency information and viewing DAS-MFCC spectrogram as image patches, the approach reached high accuracy of >99% using FSE and >97% using fiber coil on held-out test data. This system can be used for recovering the crime scene and continuously monitoring different kinds of events, such as anti-theft caused car alarm, car break-in, home break-in, fireworks in the prohibited area, etc., to protect public safety in future smart and safer city applications.

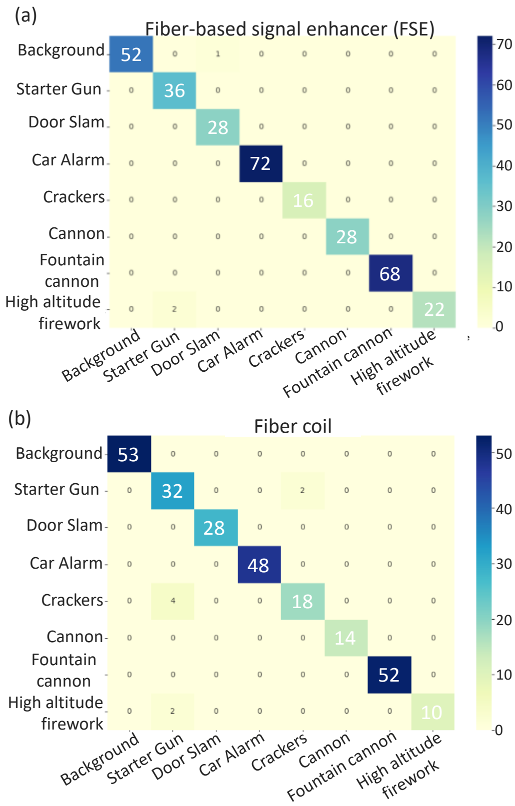

Fig. 6: Confusion matrix on (a) fiber-based signal enhancer (FSE) and (b) fiber coils.

Conclusions

To enhance public safety and security, we provided an integrated solution which combines intrusion detection from vibrational signals and impulsive event classification from acoustic signals, through a single DAS unit with dedicated cable installation schemes over existing telecom infrastructures.

The proposed system utilizes fiber sensing and deep learning techniques to analyse low-level physical parameters and detect high-level acoustic events that could pose a threat to public safety and security. By using an edge AI platform, we were able to process large-volume of DAS sensing data with low latency, allowing us to achieve real-time response. The system has demonstrated the performance in detecting and classifying events, as well as further localizing and identifying potential threats through video analytics. With continuous innovation and development, we believe that this technology has the potential to significantly enhance public safety and security.

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