Employing Fiber Sensing and On-Premise AI Solutions for Cable Safety Protection over Telecom Infrastructure

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Abstract: We review the distributed-fiber-sensing field trial results over deployed telecom networks. With local AI processing, real-time detection, and localization of abnormal events with cable damage threat assessment are realized for cable self-protection. © 2021

1. Introduction

Telecom carriers have built large-scale fiber infrastructures over the past 30 years to support Internet traffic growth, especially for coming 5G and beyond networks [1]. Although ordinary transmission fibers intended for only solo function of data transmission, it is now established to be utilized as sensing media [2, 3] by using distributed fiber optic sensing (DFOS) technologies, doubling the value of carriers' fiber assets. Lots of new applications have been created with the unique combination of fiber sensing capability and active fiber infrastructure owned by network service providers. For example, traffic monitoring and incident detection [3, 4], seismic monitoring [5], environmental temperature measurement [6] and cable localization [7] are reported.

While operational telecom fiber networks provide tremendous potential to optical sensing applications, the sensing technology, in turn, can be used to detect threats to the fiber infrastructure and improve its reliability. Fiber cable damage due to abnormal activities near cables happen occasionally, one major causes of the damages are constructions near deployed cables which generate vibrations with abnormal frequency components. These vibrations can be treated as a sign of a possible threat to the cable. In this paper, we reviewed some field results using fiber optic sensing and machine learning technologies for continuous monitoring an operational telecom network, to protect the cable itself. Reporting abnormal events and providing threat assessment instantaneously can allow quick actions to be taken, preventing potential damage on telecom facilities using fiber sensing.

2. System Design of Abnormal Activities and Threat Assessment with Real-time Processing

By detecting the intensity change of Rayleigh scattering via interferometric phase beating in fiber, fiber optic sensing technology senses any vibrations near a fiber cable and generates a large volume dataset. Processing data locally with an on-premise AI infrastructure reduces cost in data transmission and storage and also enhances data privacy. Most of the sensed vibrations are caused by normal activities such as road traffic. When the sensed vibration patterns cannot be attributed to any normal activities, a warning alarm shall be triggered. Fig. 1 shows a computationally light-weight cable safety protection system, which includes an abnormal detection module and a threat assessment module. After receiving the field sensing data, strong vibration points are first filtered out by a saliency detector. To accommodate the fluctuation of background noises, an interquartile range (IQR) based metric is adopted for adaptive thresholding in which vibrations fall above the 3rd quartile by more than 1.5 × interquartile range are determined as saliency points. Accordingly, dense spatial-temporal sensing data is reduced to a sparse format, such that abnormal detection can be conducted on-the-fly with low latency. Second, the cause of a group of salient points is determined collectively based on their spatial-temporal relationships. Different from normal traffic which mostly induces linear slopes, road construction machine could generate ripple and strip patterns, respectively. Such patterns can be recognized using specially designed detectors based on the footprints of wave propagation. The threat level of the detected abnormal event is further assessed based on time-frequency representations [8, 9]. The exponential decay rate varies at different

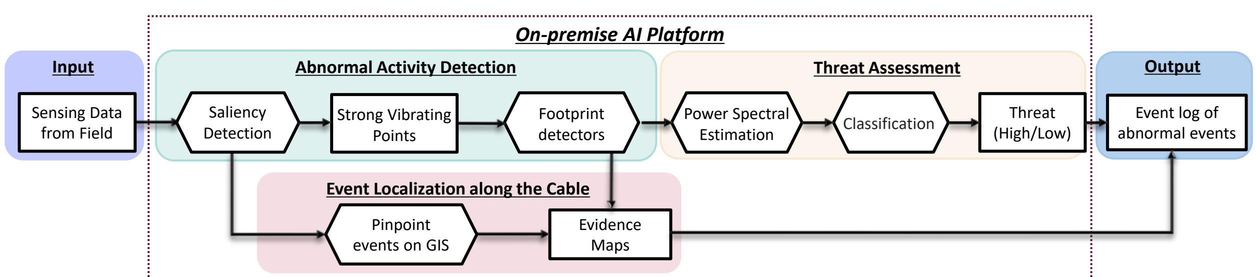


Fig. 1: Flow chart of the cable safety protection system.

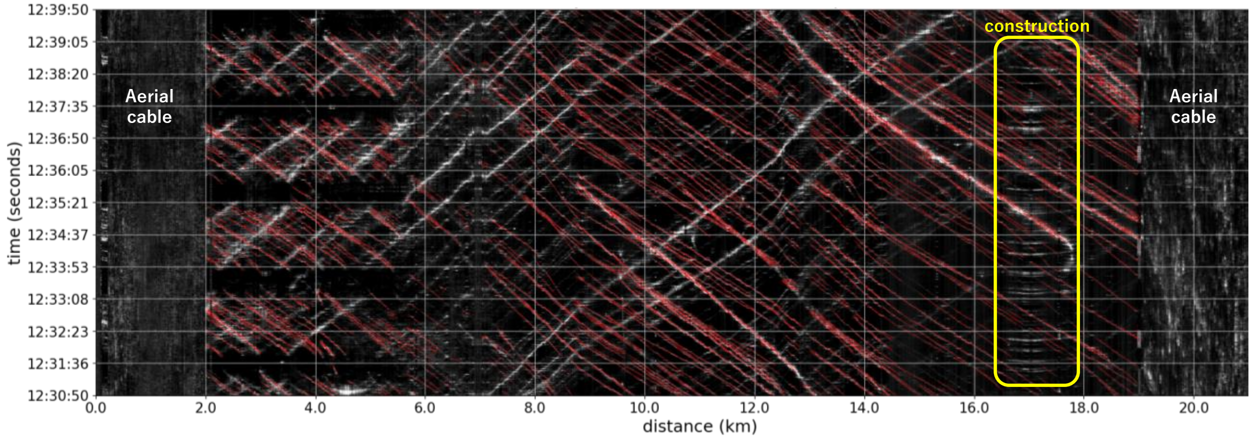


Fig. 2: Received field sensing data with normal events (road traffic) and abnormal events (construction). White/red lines: extracted traffic traces.

frequencies. The location of the detected events along the cable can be pinpointed on the map accurately [7]. High-level summary results are stored in an event log for future analysis.

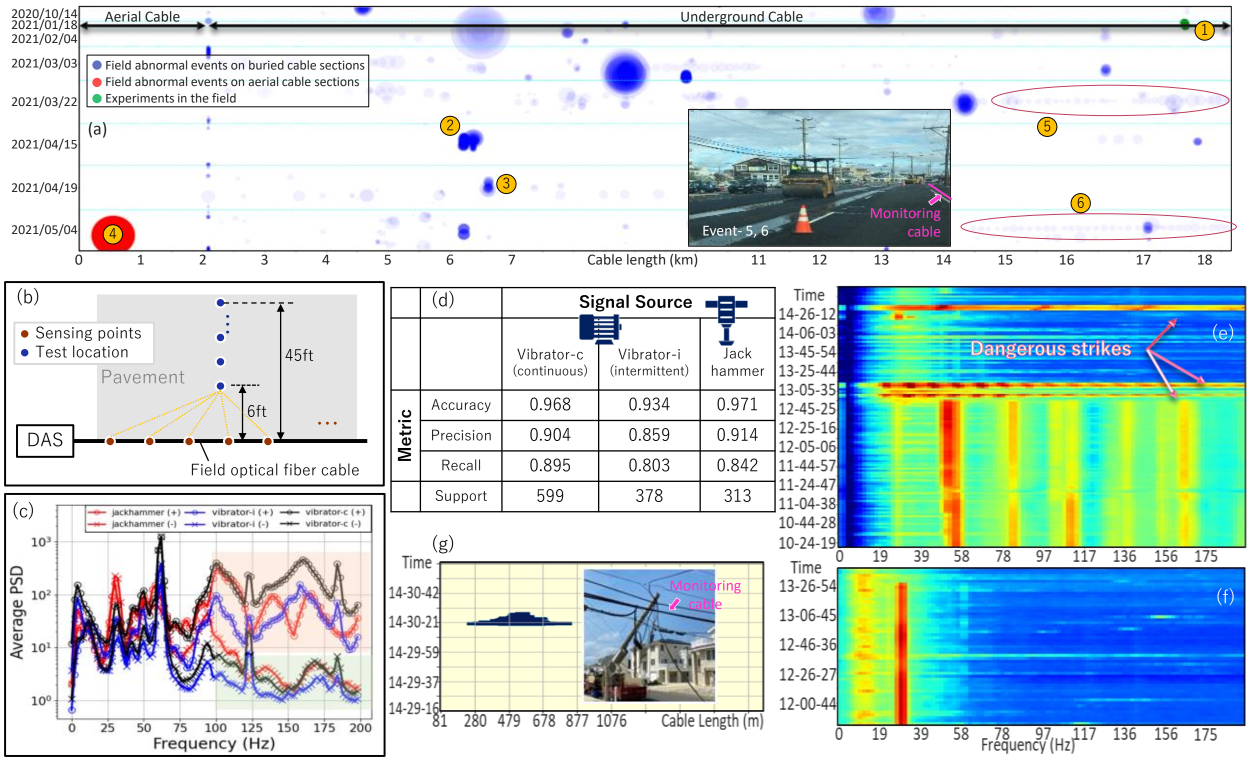
3. Field Results

The feasibility of the system is demonstrated in field trials. The tested location is a route in a metro network near Surf City, NJ, USA, with a length of 21 km includes 4-km aerial cables and 17-km underground cables. The distributed acoustic sensing (DAS) is placed in a remote site and connected to one strand fiber in the cable which has multiple-fiber inside and buried underground at depth of 30 – 60 inches. Fig. 2 shows the waterfall traces in a 9-minute window (vertical axis) and locations (horizontal axis) of the route. The aerial cables are located at the first and last 2 km. The extracted vehicle trajectories of N-bound and S-bound traffic were represented in white and red lines which considered as normal events. Around 17 km, there was a construction activity which was recognized as abnormal events from the AI platform automatically and reported to the operator with the threat assessment.

Fig. 3 shows field results of the cable safety protection system. Fig. 3(a) presents abnormal activities discovered (from both aerial and buried cables) and displayed on an evidence map. As an example, 8 days within a 7-month period were selected. Blue, red, and green circles represent field constructions, aerial cable anomalies, and field experiments, respectively. The abnormal score of the events is denoted by the size and brightness of the circles (e.g., higher risk events are denoted by larger and darker circles). Frequency-dependent attenuation mechanism is applied to determine whether the event is a high threat or a low risk to the cable. Event-1 in Fig. 3(a) is a field experiment. Fig. 3(b) illustrates the setup with test locations from 6 ~ 45 ft with the interval of 3 ft. The sources signals are a vibrator to emulate the machine engine noise and one jackhammer to simulate pavement breaking. Three modes of vibration were generated: (1) vibrator with continuous mode (*vibrator-c*), (2) vibrator with intermittent mode (*vibrator-i*), and (3) jackhammer with intermittent mode (*jackhammer*). The average PSD by Welch's method [10] is shown in Fig. 3(c) with two groups: 6 ~ 12 ft ("+", high threat), and 15 ~ 45 ft ("–", low risk). Supervised learning models can be trained to automatically pick up discriminative frequency components, such that events within or outside the 12-ft radius can be classified accurately. Based on this observation, a linear support vector machine (SVM) classifier was jointly trained on 1206 segments of signal from all three modes, and tested separately on each mode using (non-overlapping) held-out segments. Preliminary results in Fig. 3(d) show high detection rate (recall) and low false alarm rate (1– precision). The trained classifier generalizes to all the three different types of signal sources, although they exhibit distinct characteristics in the time domain. The method was validated by field constructions (Event-2 and Event-3). In the power-spectrum shown in Fig. 3(e) and 3(f), Event-2 had more high frequency components (with three dangerous strikes) than Event-3, despite also comprising strong vibrations as indicated on the evidence map, which had only low frequency components. The threat assessment module assigned higher risk to Event-2 than Event-3. Fig. 3(g) shows an incident where a falling pole fell directly on the monitoring cable (Event-4), which was caused by a construction accident at 14:30:21on May 4. Event-5 and 6 were asphalt paving machines active at 8-m away, parallel to the cable. They were detected and assessed as low risk events. Abnormal scores on the map indicate high risk events, which may cut or damage the cable. With fiber optic sensing technology, such events can be reported to the carrier immediately. Thus, communication network downtimes can be prevented or reduced.

4. Conclusions

We have successfully demonstrated abnormal activity detection and threat assessment for cable safety protection over telecom networks. By leveraging fiber optic sensing and machine learning technologies, abnormal events can be



(d)	Signal Source		
Metric	Vibrator-c (continuous)	Vibrator-i (intermittent)	Jack hammer
Accuracy	0.968	0.934	0.971
Precision	0.904	0.859	0.914
Recall	0.895	0.803	0.842
Support	599	378	313

Figure 3: (a) Evidence map. (b-d) experimental results of threat assessment. (e-g) Field results of detected abnormal events.

discovered and pinpointed at any point along fiber routes. The continuous monitoring system dealt with variations caused by various environmental factors such as weather and ground conditions based on self-normalization. The edge AI platform ensures low-latency so that timely actions can be taken. Additionally, the protection system is promising to evaluate the threat level based on distance to the cable by frequency-dependent attenuation mechanism. Once an event with high risk is discovered, a critical warning alert can be sent out to operators immediately. The field trial results show that the system can help telecom carriers to identify threat constructions near their cables in real time and prevent cable damages, which has great benefits for large scale fiber infrastructures supporting 5G and beyond networks.

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