A real-time algorithm for train position monitoring using optical time-domain reflectometry

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***Abstract*—We propose an algorithm which uses an optical time-domain reflectometer (OTDR) for real-time tracking of trains. OTDR sensing, often also termed distributed acoustical sensing (DAS), measures the Rayleigh backscattering of a light pulse along an optical fiber. The resulting signal provides information on local acoustic pressure at linearly spaced positions along the fiber. While different approaches for train tracking with DAS are described in the literature, the results have been evaluated only for short time recordings with few train crossings. In this paper we provide details on the tracking performance of a novel algorithm that finds and tracks trains over 15km. Furthermore, this is the first contribution that uses ground truth data to assess the performance of the method. For the evaluation two one hour recordings are used.**

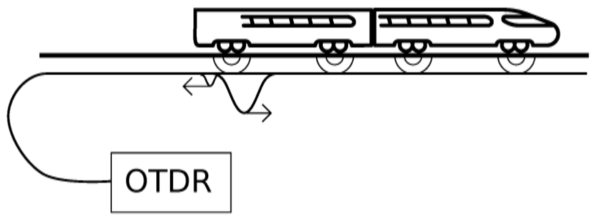

Fig. 1. As the train is moving along the track it emits vibrations that are transmitted to the optical fiber. These vibrations cause a change in the refractive index of the fiber and cause a specific backscatter, which is traveling back to the OTDR device. The measured backscatter is then captured as the DAS measurement.

I. Introduction

For safety and monitoring purposes it is compulsory to know the position of every rail vehicle at any given point in time. Several systems are available for monitoring railway infrastructure, some of them are vehicle-borne and others are installed on the track. The installation of such systems is often very costly, therefore the installation is often limited to high priority tracks. Examples for such systems can be found in [1]. In this contribution we use a fundamentally different method for tracking trains. We use distributed acoustic sensing (DAS) for train identification along the tracks. DAS signals are acquired using an optical fiber next to the railway track and an optical time domain reflectometer (OTDR). This technology measures changes in pressure exerted at linearly spaced positions along the optical fiber over time, hence the term distributed acoustic sensing. The underlying physical principle is Rayleigh scattering. The OTDR injects light pulses into the fiber at a constant rate and measures the backscatter for each individual pulse over time. Considering the speed of light the measured backscatter at a given point in time can be attributed to a certain position in the fiber. Consequently, the time resolution of the recorded data is determined by the repetition rate of the light pulses and the spatial resolution is determined by the rate with which the OTDR acquires measurements of the backscatter (Fig. 1).

This technology can monitor several tens of kilometers with a temporal sampling rate of a few kilohertz. It is also worth mentioning that the optical fiber is passive, i.e. it requires no separate power. The only active component in the measurement system is the OTDR device which keeps the maintenance costs low. Furthermore, optical fibers are often installed with modern rail infrastructure for signaling and data transfer. DAS sensing has been used for a variety of different applications, such as monitoring of pipelines for leakage or perimeter protection [2], [3], as well as for train tracking [4], [5] and railway activity monitoring [6]. While the research currently available has inspected rather short examples with only one train recorded over only a few minutes, we will test our algorithm on two recordings of one hour each with several trains and crossings. We will further compare our results to ground truth available through the tracking of the times the trains pass the signals along the track. We show that with our tracking system we can reach an average accuracy of 35 meters for 15 trains, which is beyond the state of the art. This accuracy is in the range of the accuracy of the ground truth data that is available to us. To our knowledge this is the first algorithm for train tracking in DAS data that proves robustness in a recording over a long time period with several trains crossing with validation against ground truth data.

A. DAS Measurements

For data acquisition we used a phase OTDR interrogator, for details we refer to the corresponding patent [7]. To evaluate the influence of different parameters we recorded two datasets with slightly different setups. Through this variation we can

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TABLE I
PARAMETERS FOR THE TWO DAS DATASETS

	First recording	Second recording
Observed cable length	13481m	17484m
Recording time	2709s	4487s
Number of segments	19825	25712
Spatial resolution	0.68m	0.68m
Sampling rate	4000Hz	2000Hz

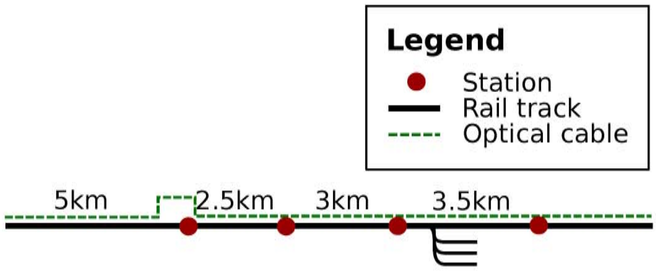

Fig. 2. There are four stations along the monitored track. Around the first station the optical cable is further from the track resulting in a weakened signal. Between the third and the fourth station is a shunting yard.

show that our algorithm is performing well with both settings. The two parameter configurations are summarized in Table I.

The train infrastructure used for recording is close to Vienna, Austria. It is a straight track with four stations, c.f. Fig. 2. It is important to note that the way the optical cable is laid has a large influence on the resulting signal. The distance between the cable and the railroad track has an influence on the amplitude of the recorded signal. If the distance becomes too large the vibrations from the trains are not strong enough anymore to see them in a DAS recording. Another source of difficulty for the tracking of trains arises when several trains move at the same time. This can lead to problems especially when trains overlap and change direction frequently as in shunting yards.

II. TRAIN TRACKING USING DAS

In the following we describe our method for tracking trains using raw OTDR data and compare it to the methods in the literature. The algorithm is divided into two main steps. In the first step we use a novel method to detect the beginning and the end points of trains based on the vibration pattern of trains. In the second step these points are used for extracting attributes from trains i.e. position, speed and length for the given second. In the following we will explain the principle of these two steps. Since a very detailed description of the tracking algorithm is out of scope for this contribution we refer to [8].

A. Train Classification

The classification of train and background signals relies on the fact that the spectral composition differs considerably between these two classes. In contrast to the literature we develop a method that only relies on the spectral pattern and avoids thresholds to make the algorithm independent of the

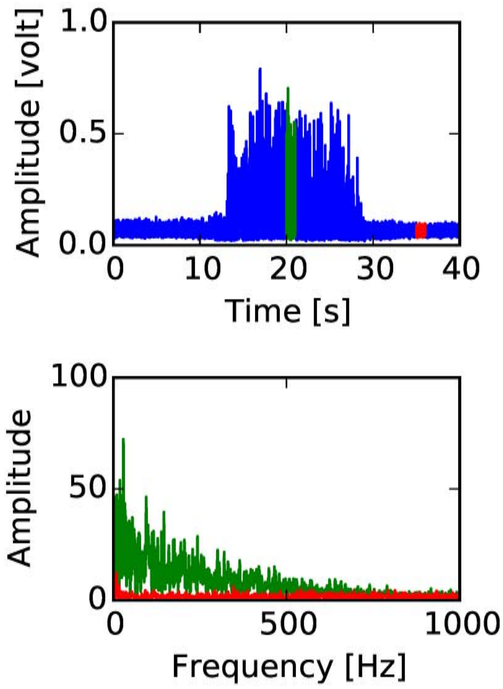

Fig. 3. The top plot shows a raw DAS signal for 40 seconds, between 12 and 29 seconds vibrations from a train are present. One second of the train signal is colored in green and one second of the background is colored in red. The bottom plot shows the Fourier transforms of the two colored portions of the raw data in the respective colors. It is clearly visible that the Fourier transform of the train signal has a very different structure form the Fourier transform of the background signal.

signal level. Data from one second at each cable segment are Fourier transformed to get the spectral distribution of the signal, see Fig. 3. The difference in the Fourier transforms between background and train signals is mainly in the frequency channels corresponding to frequencies lower than 1000. Therefore we use the absolute values of the Fourier transform as features for the classification. To reduce the number of features for the classification the frequency space is divided into 10 bins and the coefficients in these bins are summed and normalized with the sum of all coefficients.

Based on the 10 dimensional feature vector we apply a dimensionality reduction using Principal Component Analysis (PCA) using only the first two eigenvalues. It is important to note here that, while classification without PCA is performing slightly better, the processing speed is greatly improved by a dimensionality reduction. The reduced feature set containing two eigenvalues is used to train a Support Vector Machine (SVM) with a radial basis function kernel to obtain a decision boundary in two dimensional space. To obtain a sufficiently large amount of raw data for training the SVM, we annotated from the first 1500 seconds 20000 background and 20000 vibration samples of raw data in our first recording. Using the half of the annotated data for cross validation of the classification we obtain rates of 99.6 percent correctly classified feature vectors.

B. Train Tracking

Train tracking has not yet been investigated for long DAS recordings. Nevertheless it is a crucial step for analyzing real world recordings and reliable tracking across train crossings.

The binary classifications we obtain as described above are then used to track trains. The last 10 seconds of classification results are summed in time for each cable segment to get a value between 0 and 10. Gaussian filter is applied across the cable segments to smooth the values after summing. Thresholding and edge detection is applied to find the front and the rear of trains at the given second. The correspondence between trains end their edges is solved as an optimization problem, where a weight is defined between edges and trains based on their attributes e.g. distance or velocity. The optimization problem is solved with greedy heuristics. The output of the train tracking is a list of attributes e.g. position, speed and length for each train.

While the algorithm described above for tracking trains is designed to run in real-time it will only track the trains with a certain delay. The current implementation has an estimated systematic delay of 5 seconds, which arises from the summation of the classifications from the last 10 seconds.

III. Results

For evaluating the performance of the DAS based train tracking we compare our results to the available ground truth data. We furthermore give a visual interpretation of the results since the ground truth data and the DAS tracking can only be perfectly matched at two points along the monitored track.

A. Available Ground Truth Data

When a train passes a signal along the track it is automatically registered and the time the train passes is stored in a train tracking system. These data contain point based passing times for each train vehicle traveling along the track. To be able to link cable segments to track kilometers a hammer has been used to produce vibrations at given points on the track that can then be measured by the OTDR, c.f. Fig. 4. Since this procedure is time intensive and requires safety precautions only a small portion of around 1.5km has been calibrated.

Within the calibrated stretch there are two sensors in each direction registering trains. For the positions of these signals we know the exact cable segment numbers.

The train registration times are accurate to one second. With trains moving at around 120 kilometers per hour this corresponds to an accuracy of around 33 meters in distance in space.

B. Visual Evaluation of DAS Tracking

While it is not possible to evaluate the performance of the tracking for the whole length of the monitored cable, it is still possible to assess some criteria visually. Fig. 5 shows the tracking results and ground truth data. It is, first

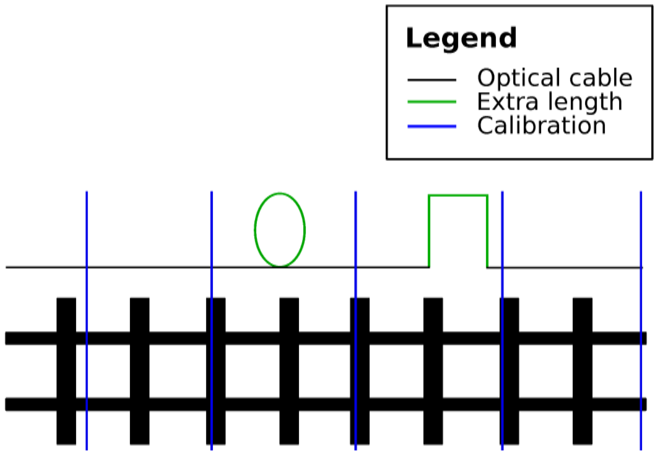

Fig. 4. Illustration of the calibration of the track. At the positions with vertical blue lines a hammer is used to create vibrations and at the same time the cable is monitored to see in which cable segment the vibration is recorded. Between two calibration points the cable segments are assumed to be arranged linearly. This is only an approximation when extra lengths, such as loops, are present in the cable. The illustration shows two extra lengths, the first one is a loop and in the second case the cable does not exactly follow the train tracks.

of all, important to note that all the trains are found by the system. There are two different sources of problems in the data available to us. Before the first station on the track the DAS signal disappears for around 1200 segments. This is probably attributable to the fact that the cable is further from the vibration source around this station. While the tracking algorithm is still able to reliably track rail vehicles across the gap, the tracks are unreliable in that section. The second source of wrong tracks is a shunting yard that is located between the 3rd and 4th station of the monitored section. While the first recording is not affected by this since no trains were shunted at the time of the measurements, in the second recording we see strong artifacts where this station is. This leads to wrong tracking results in the affected region, see Fig. 6. With our tracking algorithm it is presently not possible to reliably track trains across such scenarios. In the future we plan to extract unique features for each tracked train to be able to connect tracks across stretches with high uncertainty such as shunting yards.

C. Comparison of DAS Tracking to Ground Truth

We compared our tracking algorithm with ground truth data in two ways. First the speed of trains were computed between the two railway signals. The distance between the given two railway signals is known and the time difference was obtained from the closest tracking point to these signals. Table 5 shows the obtained speed values for each train for the reference ground truth and the tracking algorithm. The second evaluation was performed using Leave-one-out cross-validation (LOOCV). The tracking and ground truth data between the two railway signals were used in this process. For the training process the average of time delta is computed from the tracking and ground truth points of $n-1$ trains.

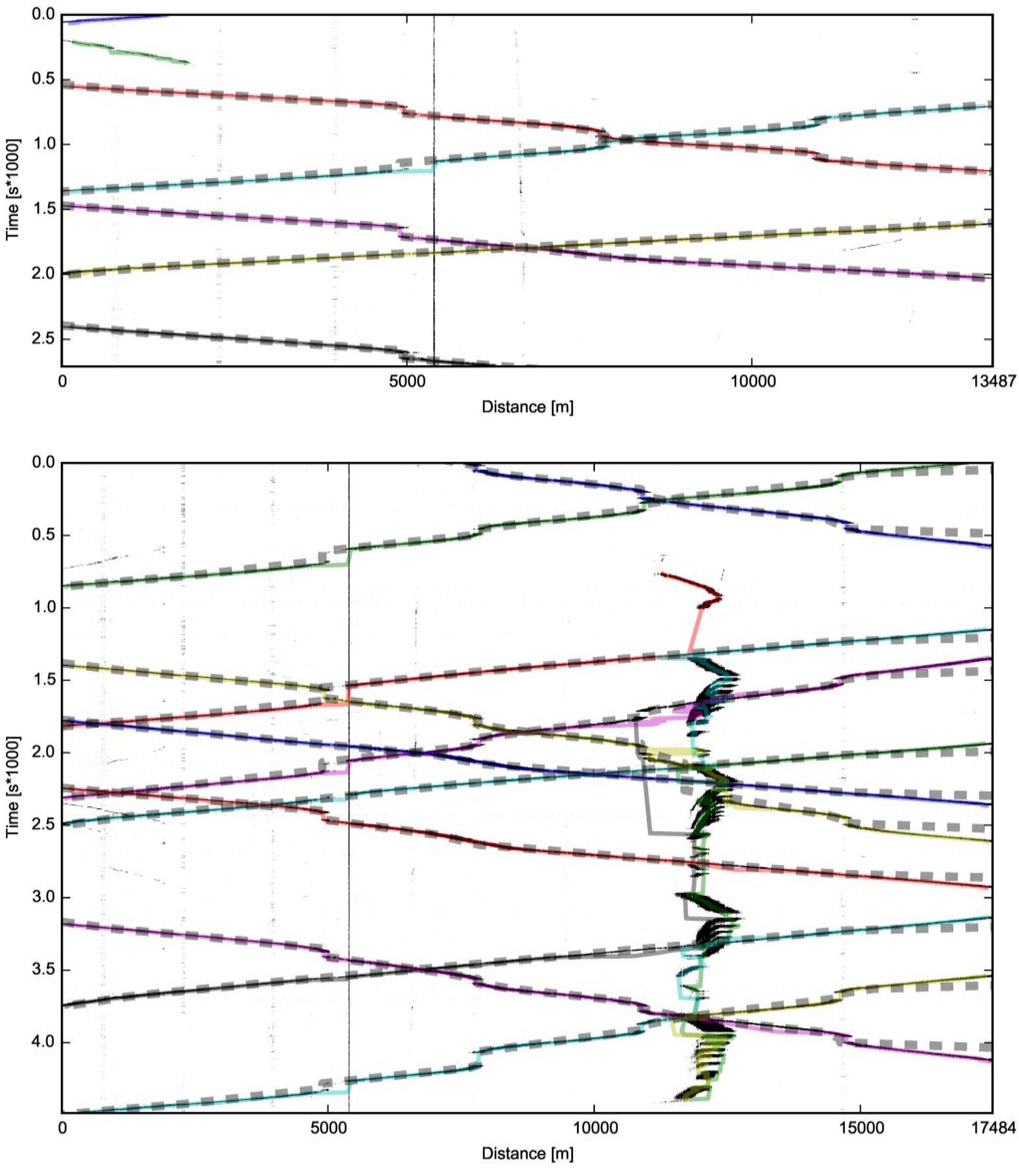

Fig. 5. Visualization of the detection and tracking for the two recordings, where each tracked object is encoded with a different line color. The ground truth data are visualized with light gray dashed lines. The image shows that all the trains are found and tracked. Underlying the tracked trains and the ground truth tracking the detection of vibrations is plotted in black. Vertical lines with vibrations can be seen, e.g. at distance around 5000, which are false positives from other vibrating objects e.g. railway equipment or cars crossing bridges over the monitored track. In the top plot in the first 500 seconds the track of a car driving next to the train tracks is visible in green. On the bottom, the shunting yard can be seen between distance 10000 and 15000, where the implemented tracking becomes unreliable. Note the different scaling of the x-axes in the two plots coming from different recording lengths in the two datasets. The two datasets were recorded with one minute offset to change the parameters of the recording device.

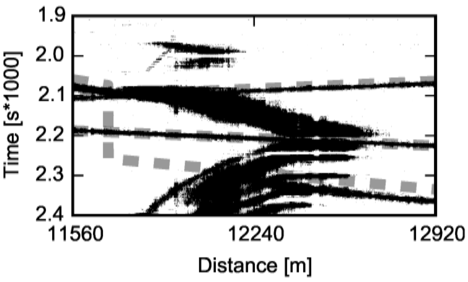

Fig. 6. Visualization of a slice from bottom image in Fig. 5 with a shunting train. We observe the following trains: a shunting train moves at distance 12000m and 2000 seconds; a cargo train enters at 2100 seconds and the vibrations of both trains start overlapping; a passenger train enters at 2200 seconds and between the distances 12000m and 12500m all three trains overlap; the cargo train leaves shunting yard after the second 2300 and finally shunting is continued backwards. Our tracking algorithm is not reliable in such scenarios as it is not clear which train leaves the overlapping section.

TABLE II
EVALUATION OF TRAIN TRACKING PERFORMANCE.

Train Id	Ref.	Tracking	Ref.	Tracking	Position Error
	(m/s)		(km/h)		(m)
23468	36.26	32.61	130.55	117.40	38.20
29515	-31.43	-32.62	-113.14	-117.45	13.13
2330	29.36	26.99	105.69	97.18	38.36
73	-33.33	-34.24	-120.00	-123.25	42.22
23488	28.67	25.53	103.23	91.90	51.79
29535	-33.33	-34.84	-120.00	-125.44	18.12
2337	-32.35	-34.39	-116.47	-123.81	41.19
103	-31.43	-32.42	-113.14	-116.71	33.50
29555	-26.83	-28.19	-96.59	-101.49	20.08
23508	31.62	26.33	113.82	94.79	56.94
90093	-26.19	-27.09	-94.29	-97.52	8.76
76	30.82	28.54	110.97	102.75	42.55
2334	34.25	30.72	123.30	110.58	53.05
29575	-32.35	-33.87	-116.47	-121.92	31.16
23528	30.82	28.78	110.97	103.60	42.95

The validation computes the average of the absolute spatial distance from the tracking points of the left out train. The average of the absolute distance error was 21 meters. Table II shows the obtained distance error for each train, as well as the speed computed from our tracking and the speed computed from the reference data.

As discussed, the reference data accuracy is only down to one second corresponding to approximately 33 meters in position given the train speed of approximately 120 kilometers per hour. Since we use two points to evaluate the positional error, the ground truth data provides an accuracy down to approximately 66 meters. Table II shows that all the positional errors are within the expected range. To assess the tracking performance with higher accuracy a different source of ground truth data has to be used.

IV. CONCLUSION

The work presented in this paper shows that trains can be reliably tracked using DAS measurements. The presented system is a low maintenance alternative or a back up for other train tracking systems installed. For assessing the tracking performance of the algorithm two recordings were used with a duration of 2709 seconds and 4487 seconds, respectively. The accuracy of the presented algorithm was in the range of the uncertainty in the given ground truth data, which is at around 33 meters for each point.

Train tracking showed to be stable and reliable on the open track with train crossings when the optical fiber is picking up the vibrations of trains passing. Tracking trains close to a shunting yard was prone to error, as the fiber is picking up the superposition of the vibrations from different trains. Any source of vibrations close to the fiber can possibly have an influence on the tracking performance. If the fiber is positioned too far from the train tracks the vibrations are not strong enough anymore to identify trains. The described problems can be avoided by evaluating the layout of the train tracks and the optical fiber before installing a DAS train tracking system.

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