

Instant Location Detection of Objects Moving at High-Speed in C-OTDR Monitoring Systems

Andrey V. Timofeev

Abstract—The practical efficient approach is suggested to estimate the high-speed objects instant bounds in C-OTDR monitoring systems. In case of super-dynamic objects (trains, cars) is difficult to obtain the adequate estimate of the instantaneous object localization because of estimation lag. In other words, reliable estimation coordinates of monitored object requires taking some time for data observation collection by means of C-OTDR system, and only if the required sample volume will be collected the final decision could be issued. But it is contrary to requirements of many real applications. For example, in rail traffic management systems we need to get data of the dynamic objects localization in real time. The way to solve this problem is to use the set of statistical independent parameters of C-OTDR signals for obtaining the most reliable solution in real time. The parameters of this type we can call as «signaling parameters» (SP). There are several the SP's which carry information about dynamic objects instant localization for each of C-OTDR channels. The problem is that some of these parameters are very sensitive to dynamics of seismoacoustic emission sources, but are non-stable. On the other hand, in case the SP is very stable it becomes insensitive as rule. This report contains describing of the method for SP's co-processing which is designed to get the most effective dynamic objects localization estimates in the C-OTDR monitoring system framework.

Keywords—C-OTDR-system, co-processing of signaling parameters, high-speed objects localization, multichannel monitoring systems.

I. INTRODUCTION

THE high-speed objects real-time reflection in C-OTDR monitoring systems [1]-[4], [7] is quite often problem in various applications. In particular, C-OTDR-systems usage for rail traffic management is very perspective as reasonable alternative to traditional track circuits—systems. The C-OTDR approach is based on the use of the high vibrosensitivity of the infrared energy stream injected into ordinary optical fiber (buried in the ground near the railways) by means of semiconductor laser of low power. This optical fiber will be called a distributed fiber optic sensor (DFOS). Typically DFOS length is 40-50 km. In the systems of this class, all relevant information is transferred to Processing Center (PC) by the optical fiber which is not only a sensor but at the same time an effective and reliable channel for ordinary data transmission. We will call the systems of this class as optical fiber classifiers of seismic pulses (OXY), which by the principle of operation belong to the multitude of so-called C-OTDR systems at the same time, the high-speed objects real-time reflection in C-OTDR monitoring systems is not easy

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task because for each channel exist the lag of statistical estimation. So, it is take some time to collect the sample size which is enough to provide acceptable reliability. But in many real applications it is necessary to getting of dynamic objects localization in real-time. For example, this necessity exists in rail traffic management systems, where we have to have an actual localization point of trains each second. The reasonable approach to this task solution in framework of C-OTDR monitoring systems is based on usage the set of statistical independent parameters of C-OTDR signals provided that all those parameters have to be calculated in one cycle of monitoring for each of C-OTDR channels. We denote these parameters as “signaling parameters” or SP. It is important that each SP is calculated for respective C-OTDR-channel therefore each SP corresponds to a particular C-OTDR-channel. Roughly speaking, each SP has two basic states: “state 1: the targeted seismoacoustic emission source exist in vicinity of C-OTDR channel”, “state 0: the targeted seismoacoustic emission source not exist in vicinity of C-OTDR channel”. The basic feature of SP is to quickly change its state from the “State_0” to the “State_1” in case if targeted seismoacoustic emission source appear in vicinity of respective channel and vice versa. The problem is that each of SP's has different sensitivity and stability. A SP-sensitivity is an ability to quickly respond on appearing seismoacoustic wave in vicinity of respective C-OTDR channel. Simply put, the more the first derivative of SP in respective channel in moment of achievement of a dynamic object to this channel is, the better SP-sensitivity is. On the other hand, SP-stability is an ability to hold the SP value in stable state “State_1” until the source of seismic acoustic emission exists in vicinity of the respective channel and vice versa. This report contains describing the method for SP's co-processing which designed to get the most effective dynamic objects localization estimates in the C-OTDR monitoring system framework. The goal of this co-processing is to get the integral SP with optimal parameters of sensitivity and stability.

II. STATEMENT OF THE PROBLEM

Let us assume that we have a multichannel C-OTDR monitoring system. There are array of statistically independent channels, which are used for getting targeted signals. Indexes of system channels in conjunction form a set $Z=\{1,2,\dots\}$. Observations are made at successive times, which form a set $T = \{t_1, t_2, \dots\}, \forall i > 0 : t_{i+1} - t_i = \Delta t > 0$. Let us denote: τ_j is random moment time, $\tau_j \in T$. So, τ_j is the moment of abrupt change of the observations distributions in j -th channel? This

change happened due the targeted seismoacoustic emission source signal appearance. Actually, τ_j is the **direct change-point moment** [5], [6] of observation distributions. This time moment coincides with the moment of appearance of seismoacoustic emission source near j -th channel. On the other hand, the moment $\bar{\tau}_j$ is the **reverse change-point moment**. This time moment coincides with the moment when seismoacoustic emission source disappeared from j -th channel.

For each channel $j \in \mathbf{Z}, t \in T$ the set $\mathbf{SP}_j(t)$ of signaling parameters are defined. So, $\mathbf{SP}_j(t) = \{S_j^{(i)}(t) \mid i = 1, \dots, m\}$. We have:

$$\begin{aligned} \forall t < \tau_j - \lambda_D, t \in \Delta : S_j^{(i)}(t) &= \theta_j^{(i)} + \sigma_j^{(i)}(t)\zeta_j^{(i)}(t) \\ \forall \tau_j - \lambda_D \leq t < \tau_j, t \in \Delta : S_j^{(i)}(t) &= \theta_j^{(i)} + \sigma_j^{(i)}(t)\zeta_j^{(i)}(t) + \\ &F_D^{(i)}(t \mid \tau_j - \lambda_D), \\ \forall t \geq \tau_j, t \in \Delta : S_j^{(i)}(t) &= \theta_j^{(i)} + \sigma_j^{(i)}(t)\zeta_j^{(i)}(t) + \\ &\theta_{s,j}^{(i)}(t) + \pi_j^{(i)}(t)\xi_j^{(i)}(t). \\ \forall \tau_j < t < \bar{\tau}_j + \lambda_R : S_j^{(i)}(t) &= \theta_j^{(i)} + \sigma_j^{(i)}(t)\zeta_j^{(i)}(t) + \\ &F_R^{(i)}(t \mid \bar{\tau}_j + \lambda_R), \\ \forall t \geq \bar{\tau}_j + \lambda_R, t \in \Delta : S_j^{(i)}(t) &= \theta_j^{(i)} + \sigma_j^{(i)}(t)\zeta_j^{(i)}(t) \end{aligned}$$

Here $\{\zeta_j^{(i)}(t)\}, \{\xi_{s,j}^{(i)}(t)\}$ are mutually independent random variables,

$$\begin{aligned} \mathbf{E}\zeta_j^{(i)}(t) &= 0, \mathbf{E}(\zeta_j^{(i)}(t))^2 = 1, \mathbf{E}\xi_{s,j}^{(i)}(t) = 0, \mathbf{E}(\xi_{s,j}^{(i)}(t))^2 = 1, \\ \sigma_j^{(i)} &\leq L_N, \pi_j^{(i)} \leq L_S, \\ \forall t \in (\tau_j - \lambda, \tau_j) : 0 < F_D^{(i)}(t \mid \tau_j - \lambda) &\leq \theta_{s,j}^{(i)}(t), \\ \forall t \in (\bar{\tau}_j, \bar{\tau}_j + \lambda_R) : 0 < F_R^{(i)}(t \mid \bar{\tau}_j + \lambda_R) &\leq \theta_{s,j}^{(i)}(t) \end{aligned}$$

Further

$$\forall \theta_k^{(i)} \neq \theta_j^{(i)}, \Xi_{s,j}^{(i)}(t) = \theta_{s,j}^{(i)}(t) + \pi_j^{(i)}(t)\xi_j^{(i)}(t)$$

is equation of target signal in j -th channel, $\theta_{s,j}^{(i)}(t) > 0$. The constants L_N, L_S are unknown; background noise parameters $\{\theta_j^{(k)}\}$ are unknown a priori too; λ_D s time parameter of precursor impact $\lambda \sim 5$ -10 sec. The $F_D^{(i)}(t \mid \tau_j - \lambda_D)$ is precursor of high-speed moving object with enormous mass (train). On the other hand, the $F_R^{(i)}(t \mid \bar{\tau}_j + \lambda_R)$ is aftereffect of the high-speed moving object with enormous mass (train). The

precursor/ aftereffect power is dependent of object speed, the absorption coefficient of the medium, and on the train wheels condition. So, sources of that kind affect to the respective channel for a long time:

- (in case of precursors) before these sources reach this channel de facto (100 and more meters).
- (in case of aftereffect) after that, as these sources leave this channel de facto (200 and more meters).

Components $F_D^{(i)}(t \mid \tau_j - \lambda_D), F_R^{(i)}(t \mid \bar{\tau}_j + \lambda_R)$ do some problems in process of the high-speed objects localization.

The research objective is to build the procedure, which will determine the **channel** in which the front edge of the dynamic object is located at the time moment t with using only $\mathbf{SP}_j(t)$ (real-time regime). In other words, this channel completely determines the localization of the front edge monitored object.

III. SOLUTION METHOD

The fundamental difficulty of moving objects localization task is connected with lack of prior information. Really in case of rail traffic management systems, we have not any information about statistical distributions of SP, we have not any data about dynamic parameters of moving objects (trains), and we have not any prior data about types of moving objects (about train types). It would seem, representative statistical distributions of SP can be collected for a long time observation at special polygon. But in this case the problem arise with high variability of noises parameters of trains, which radically dependent of wheels status. In this connection we have to use empirical approaches for localization task solution. Those approaches are based on clear physical representations and practical models. One of similar approaches is the model of "ideal train signal" in form of generalized Heaviside step function $\delta(x)$. In this case we can use the approach based on of the maximum of correlation function to estimate the train's instant localization. Let us consider the following simple correlation statistics for i -th SP:

$$\vec{\Phi}_i(\varepsilon \mid t, j, a) = \sum_{k=j-a}^{j+a} S_k^{(i)}(t)\delta(k \mid j - a + \varepsilon), \quad (1)$$

$$\vec{\Phi}_i'(\varepsilon \mid t, j, a) = \sum_{k=j-a}^{j+a} S_k^{(i)}(t)(1 - \delta(k \mid j + a - \varepsilon)). \quad (2)$$

Here

- parameter $a > 0$ defines a size of local scale and it have to be chosen for practical reasons. As rule, in case of rail traffic management systems we use the next bounds $10 < a < 30$.

$$\delta(x \mid y) = \begin{cases} 0, & x < y \\ 1, & x \geq y \end{cases}. \quad (3)$$

In case the movement from left to right:

- the estimate of train forefront localization is

$$\varepsilon_D(t) = \underset{\varepsilon}{\text{Arg Max}} \left(\vec{\Phi}_i(\varepsilon | t, j, a) \right); \quad (4)$$

- the estimate of train trailing edge localization is

$$\varepsilon_R(t) = \underset{\varepsilon}{\text{Arg Max}} \left(\vec{\Phi}_i'(\varepsilon | t, j, a) \right). \quad (5)$$

The calculation of estimates for the movement from right to left are similar to calculation of estimates $\varepsilon_D(t)$, $\varepsilon_R(t)$.

It easy to see

$$\Delta_{ij}(t) = \left| \underset{\varepsilon}{\text{Arg Max}} \mathbf{E} \left(\vec{\Phi}_i(\varepsilon | t, j, a) \right) - j \right| > 0, \quad (6)$$

$$\Delta'_{ij}(t) = \left| \underset{\varepsilon}{\text{Arg Max}} \mathbf{E} \left(\vec{\Phi}_i'(\varepsilon | t, j, a) \right) - j \right| > 0 \quad (7)$$

because of $F_D^{(i)}(t | \tau_j - \lambda_D)$, $F_R^{(i)}(t | \tau_j + \lambda_R)$ influence. It is obvious, if $F_D^{(i)}(t | \tau_j - \lambda_D) = 0$ and $F_R^{(i)}(t | \tau_j + \lambda_R) = 0$ then $\Delta_{ij}(t) = 0$ and $\Delta'_{ij}(t) = 0$ respectively. Herein, in case of the movement from left to right (LTR-CASE):

- the maximum of functional $\mathbf{E}(\vec{\Phi}_i(\varepsilon | j, a))$ will be achieved at channel j in the moment $t = \tau_j$ (estimation of the train forefront localization);
- $\mathbf{E}(\vec{\Phi}_i'(\varepsilon | j, a)) \rightarrow \max$, if $t = \tau_j$ (estimation of train trailing edge localization) respectively.

In this case, we would have the exact solution of the localization task. Unfortunately, the components $F_D^{(i)}(t | \tau_j - \lambda_D)$, $F_R^{(i)}(t | \tau_j + \lambda_R)$ are not be zero and therefore we always have the nonzero biases $\Delta_{ij}(t)$, $\Delta'_{ij}(t)$. In process of solving the localization task we should minimize the bias value. To achieve this goal (in case of the train forefront localization) we can use the set $\mathbf{SP}_j(t)$ and formulate the solution in the following form:

$$\varepsilon(t) = \sum_i w_i \varepsilon_i(t) + b \quad (8)$$

where $\varepsilon_i(t) = \underset{\varepsilon}{\text{Arg Max}} \left(\vec{\Phi}_i(\varepsilon | t, j, a) \right)$, $\sum_i w_i = 1$, $\forall w_i \geq 0$.

Parameter b is used to compensate the bias. We have the training set in following form

$$\mathbf{S} = \left\{ \left(\mathbf{S}^{(1)}(2a, k_p | p), \dots, \mathbf{S}^{(m)}(2a, k_p | p); k_p \right)_p \mid p = 1, \dots, z \right\},$$

$$\mathbf{S}^{(i)}(2a, k_p | p) = (S_{k_p-a}^{(i)}(t | p), S_{k_p-a+1}^{(i)}(t | p), \dots, S_{k_p+a}^{(i)}(t | p))$$

are vectors of SP- samples with given that k is the number of channel in which front edge of the dynamic object is located.

Parameters $\mathbf{w} = (w_1, w_2, \dots, w_m)$ have a sense of weighting coefficients. If the $\varepsilon_i(t)$ is calculated with use the data set

$\mathbf{S}^{(i)}(2a, k | p)$ we will denote this as $\varepsilon_{i,D}(t | p)$ for LTR-CASE, estimation of the train forefront. On the training phase it is necessary to determine the values of parameters \mathbf{w} and b , which deliver a minimum of the quadratic functional

$$H_D(\mathbf{w}, b) = \sum_p \left(k_p - \sum_i w_i \varepsilon_{i,D}(t | p) + b \right)^2 \quad (9)$$

The expressions for other cases (not LTR, estimation of the train trailing edge) are obvious and therefore they do not specify here to save the paper size.

IV. USAGE OF THE SUGGESTED APPROACH IN THE REAL C-OTDR MONITORING SYSTEM

The approach described in this report is used for train's localization in frame of in a real C-OTDR monitoring system. The parameters of this system are: the probe pulse duration - 50 ns; frequency sensing - 6 kHz; update rate of models - 20 Hz; the probe signal power - 100 mW; laser wavelength - 1550 nm. This system was installed to monitor railways (Astana area, Kazakhstan). The length of the fiber optic sensor (FOS) is 1,400 m. This sensor is buried in the vicinity of real railways (offset is 5 m, depth is 50 cm). The FOS length was divided on 1,400 logical C-OTDR channels, but in the full-scale C-OTDR system there are more than 20,000 channels. Each of those channels generated the stream of primary signals (makers). In this system are three basic SP's. Namely

- $S_k^{(1)}$ (parameter "ME") is the average of speckle in channel k ;
- $S_k^{(2)}$ (parameter "SD") is dispersion of speckle in channel k ;
- $S_k^{(3)}$ (parameter "VL") is the first derivative of speckle in channel k .

The trains moved along the FOS with average speed around 40...80 km/h. Fig. 1 shows typical speckle-diagram "waterfall" of a short train. Speed of this train was around 40 km/h, and this "waterfall" corresponds to frequency band (60-150) Hz, i.e. this diagram reflects the seismoacoustic events of the frequency band (60-150) Hz. In this application area, we believe that this frequency range is a high frequency band.

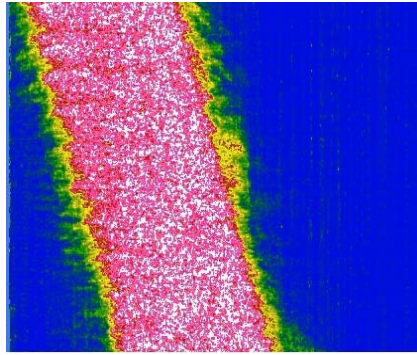


Fig. 1 The speckle-diagram of a short train

Fig. 2 shows the moving short passenger train. This frame contains three graphs, which are marked with labels “ME”, “SD” and “VL” accordingly. Here we can see the graph of parameter $S_k^{(3)}$ (marker “VL”) has a very steep leading front, minimal value of precursors/aftereffect, but non-stability of this parameter is obvious. On the other hand, the graph of $S_k^{(2)}$ demonstrates: this parameter has a high stability, some impact of precursors/aftereffect, as well as significant impact of aftereffects. The same situation has place in case of graph “ME”. Thus, data of this frame could be used to estimate of the train forefront localization only with using of “ME” and “SD” parameters. But estimation the train localization trailing edge it is possible with using of “VL” parameter only, because of aftereffects influence. Figs. 3 and 4 clearly illustrate the significant difference of stability/sensibility levels for different SP’s. Both of those frames demonstrate of the high sensibility of the parameter “VL” and its instability simultaneously.

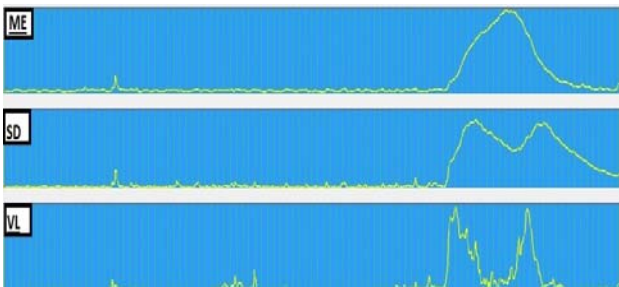


Fig. 2 Short passenger train, Frame 1

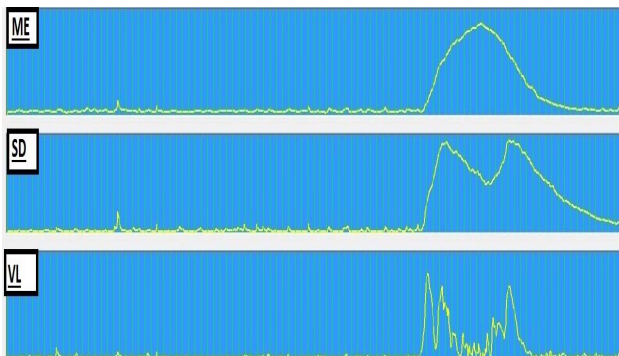


Fig. 3 Short passenger train, Frame 2

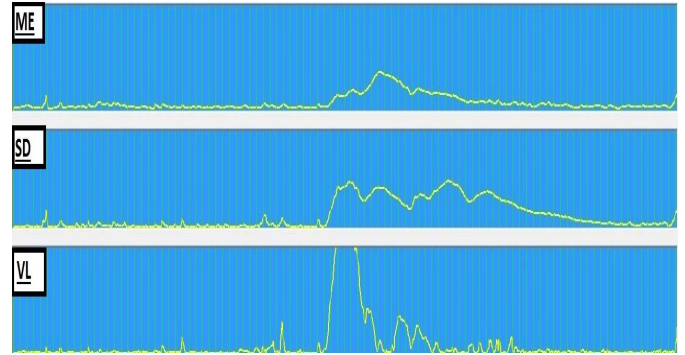


Fig. 4 Short passenger train, Frame 3

Table I shows sufficiently high practical effectiveness of the described approach to estimate the train forefront localization. In the case of cargo trains here we have the worse accuracy. It is due to the strong influence of the status of wheelsets, which are more worn out in comparison with passenger train wheelsets.

TABLE I
 THE PRACTICAL RESULTS

Type of SES	Forefront localization accuracy (m)
"passenger train" (40 km/h)	5
"shunting train" (40 km/h)	5
"passenger train" (70 km/h)	6
"shunting train" (60 km/h)	6
"cargo train" (50 km/h)	9

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REFERENCES

- [1] K. N. Choi, J. C. Juarez, H. F. Taylor, "Distributed fiber optic pressure/seismic sensor for low-cost monitoring of long perimeters", Proc. SPIE 5090, Unattended Ground Sensor Technologies and Applications, 2003, pp. 134-141.
- [2] J. C. Juarez, E. W. Maier, K. N. Choi, and H. F. Taylor, "Distributed Fiber-Optic Intrusion Sensor System", *Journal of Lightwave Technology*, Vol. 23, Issue 6, 2005, pp. 2081-2087.
- [3] S. S. Mahmoud, Y. Visagathilagar, J. Katsifolis., "Real-time distributed fiber optic sensor for security systems: Performance, event classification and nuisance mitigation". *Photonic Sensors*, Vol.2, Issue 3, 2012, pp. 225-236.
- [4] V. Korotaev, V. M. Denisov, A. V. Timofeev, and M. G. Serikova, "Analysis of seismoacoustic activity based on using optical fiber classifier," in Latin America Optics and Photonics Conference, OSA Technical Digest (online) (Optical Society of America, 2014), paper LM4A.22.
- [5] Y. Mei, "Sequential change-point detection when unknown parameters are present in the pre-change distribution", *The Annals of Statistics*, Vol. 34, 2006, pp. 92-122.
- [6] T.L. Lai, "Sequential Change point Detection in Quality Control and Dynamical Systems", *Journal of Royal Statistical Society, Series B*, Vol. 57, 1995, pp. 613-658.

- [7] A.V. Timofeev, "Monitoring the Railways by Means of C-OTDR Technology", *International Journal of Mechanical, Aerospace, Industrial and Mechatronics Engineering*, 9(5), 2015, 620-623.

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