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Emil Pricop
Grigore Stamatescu *Editors*

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# Contents

# Multimodal Heterogeneous Monitoring of Super-Extended Objects: Modern View

**Andrey V. Timofeev and Viktor M. Denisov**

**Abstract** This chapter provides modern view on the super-extended objects monitoring. The monitoring process is being reduced to the detection and classification of targeted events occurred in the vicinity of the controlled object by tracking changes in the internal state of the monitored object and by search for precursors of an environmental change, which can serve as precursors to natural and technological disasters. Suggested approach is based on the multimodal concept of the monitoring object observation, heterogeneous data fusion, detection and classification of targeted events. The approach assumes that different types of physical field are observed simultaneously in real time, data is received from different types of sensors in various rate with different accuracy, with insufficient prior information about distribution probability of targeted signals and background noises. The suggested approach provides stable detection of targeted events, which guarantees upper bounds for probabilities of type I and type II errors. Identification of targeted events type (classification problem) is based on the heterogeneous data fusion methodology. The application results of the proposed approach in the real monitoring system are presented herein.

## 1 Introduction

The problem of complex monitoring of the super-extended objects has always been of great practical importance. For example, oil and gas pipelines, railways, national frontier are examples of typical super-extended objects, and all of these facilities need to be remotely monitored. Complex monitoring provides solutions for the following tasks:

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- unauthorized activities detection (tie-into a pipeline, excavation in the monitoring object vicinity, pedestrian activity on railways, etc.);
- telemetric status check of technological equipment on the monitoring objects (deformation of pipelines, leaks detection, deformation of building structures);
- control of natural objects that form unified geotechnical-system with monitored object (soil displacement under building foundations, development of karst processes etc.);
- timely detection of technogenic or natural disasters (oil leaks, landslides, train derails, damage of railway tracks), which appear in the monitoring objects vicinity.

Solution for these problems is based on a detection of certain precursors that signal the emergence of targeted events or processes. We will call those precursors a "targeted events". Examples of targeted events: a seismoacoustic vibration accompanying the oil spill from the pipe; a seismoacoustic noise and other symptoms associated with unauthorized attempts of tie-into pipeline or excavation near the railways; seismoacoustic signals associated with pedestrian activity in vicinity of railways; seismoacoustic signals associated with landslides in region of the monitoring object localization.

Existing multimodal solutions for monitoring of super-extended objects use networks of seismic sensors to control the seismoacoustic field near of the object. This approach is becoming expensive if the object's perimeter exceeds 10 km with a system resolution of 10 m. A cost of such system will be 4–5 times more expensive then cost of the monitoring systems using distributed acoustic sensors (DAS) [1, 2]. This is due to a need to provide electrical power and radio communication for each sensor of the network. At the same time the sensors of DAS-monitoring systems have to be installed to meet a special condition: depth not less than 50 cm, offset from the monitoring object up to 5–10 m. These conditions cannot be met in all areas where monitoring objects are situated. Therefore, there is a need for integrated solutions, which means solutions using different types of sensors. Different sensors have divergent sets of specific characteristics, and they measure various physical fields with dissimilar accuracy. It entails the problems with correctness of a heterogeneous information fusion when system detects and classifies targeted events. Additional problems are connected with insufficient prior information about statistical characteristics of the signals and noises.

The approach described in this chapter is intended to provide the multipurpose multimodal monitoring based on concurrent observations of various types of physical fields (seismoacoustic, optical/IR, magnetic etc.). As it was proved by multiple experiments, a joint processing data of these systems significantly improves of the monitoring reliability. Practically effective methods of information fusion are suggested, which designed for guaranteed detection/classification of the targeted events in condition of a priori indeterminacy.

## 2 Research Objective

Monitoring systems of the super-extended objects are designed to control the operational situation in the vicinity of the monitoring object. The operational situation consists of spatial-time events (STE) flow. The STE's appear in vicinity of monitored object. In common case, STE's can have the dynamic nature; also they can form groups (flows). Obviously, the targeted events' set is a subset of the STE-set. The measurements, which were obtained from sensors of various types, are as the raw data for comprehensive analysis in the monitoring systems. The monitored object represents a distributed system of material assets. The monitoring systems are designed to control the STE's flows in vicinity of these material assets. In monitoring process, we have to detect the STE and classify the STE type (identify targeted events). STE examples are: pedestrian or group of pedestrians in vicinity of railways; technological activities, which are carried out near to material assets of monitored object (operations with heavy equipment near the oil and gas pipelines, operation of maintenance crews on the rail tracks, etc.); train traffic; cars traffic near gas pipelines; unauthorised tie-into pipelines; abrupt soil shift in the area of monitoring object; pedestrians in a vicinity of national frontier. Obviously, almost every STE is a source of seismoacoustic emission source (SES). In this connection, almost every STE may be detected and classified with usage of sensors, which measure the seismic field.

The basic goal of comprehensive monitoring of super-extended objects is the solution of the following tasks: Task "D" (Detection)—detection of the STE; Task "L" (Localization)—estimation of localization of the detected STE with simultaneous estimation of dynamics parameters; Task "C" (Classification)—classification of detected STE by means of assigning it to one of N priori given classes; Task "S" (Object Status Definition: Assessment of Risks)—evaluation of the degree of monitored object operating safety.

Priori N of targeted STE classes (types) are given, and these classes form the set of types (ST). As rule, the power of this set does not exceed a few dozen units. For various application areas ST's can be significantly different, and to have a different features. For example, technological operations on gas pipeline significantly differ to technological operations on railway tracks as in type of seismoacoustic vibrations, as well as in type of visual images. In order to monitor targeted object in area of its localization are installed sensors of different physical nature (DAS, nets of point seismic sensors, nets of inclinometers, far CCTV etc.). Data received from these sensors is heterogeneous and therefore requires a special pre-processing. Each type of sensor generates various types of STE-features, which have different informativeness level and reliability. It is therefore necessary to use a correct fusion procedure of heterogeneous data to provide an effective solution of "D", "L", "C" and "S" tasks. Moreover, solving task "D" is necessary to overcome high degree of uncertainty, which is related to probability characteristics of targeted signals and background noises. This situation is due to the fact that statistical characteristics of background noises are significantly differ around a monitoring object and at the same time, these characteristics have a dynamic nature. All of it represents a significant problem of how the detection subsystem parameters must constantly adjust to changing of background noise characteristics probability. The goal of our research is to suggest effective solutions of tasks “D” and “C”, with usage of different types of sensors placed along a super-extended monitoring object. Solution of task “L” may be reduced to an ordinary triangular task. Methods of this task’s solution are well known and are not included herein due to the article size restrictions. The task “S” solution is a separate problem, the solution of which is beyond the scope of this study. Suggested approaches for solution of tasks “D”, “C” are based on the modern data processing methods, which guarantee high performance and reliability of the monitoring system.

## 3 Architecture of Heterogeneous Multimodal Monitoring System

In this section we describe general principles of heterogeneous multimodal monitoring system architecture as well as the term “channel” of monitoring system.

### *3.1 General Principles of Heterogeneous Multimodal Monitoring System Architecture*

The method based on high vibrosensitivity of optical fiber is an effective to monitor super-extended objects [2]. In this case, the optical fiber is buried in a vicinity of monitored object, and therefore is influenced to fluctuations of the same seismic field. This fact gives possibility to control a seismoacoustic field near monitored object. So-called C-OTDR monitoring systems [2] belong to this class of systems. Acronym “C-OTDR” is disclosed as “Coherent Optical Time Domain Reflectometer”. There are three basic system units: impulse coherent laser, monomode optical fiber (distributed fiber optical sensor: DFOS), and processing unit. An impulse infrared laser sends an infrared coherent stream into a DFOS. Spreading through the DFOS, small part of the injected stream is reflected by the optical fiber imperfections. Reflected part of the stream is called Rayleigh elastic backscattering radiation. Due to a coherency, the reflected stream forms images of chaotic interference at the point of retrieval. Images of chaotic interference are called C-OTDR-speckles structures or simply speckles. These speckles are highly sensitive to vibrations and reflect even weak seismic vibrations which appear near of the DFOS. In simple words, C-OTDR-speckles “vibrates” by reason of initial vibration of seismoacoustic emission source which creates seismic waves in vicinity of DFOS (and near monitored object at the same time). So, these waves are initial reason of C-OTDR-speckles vibration, because of changes in local refractive index of the optical fiber. STE's leaves traces in seismoacoustic field, and STE's are seismoacoustic emission sources (SES) in this case. Seismoacoustic vibrations from those SES's are propagated in the ground, inducing secondary vibrations of C-OTDR-speckles with the same frequency. It is important to mention that Time-Frequency Characteristics (TFC) of C-OTDR-speckle vibrations are similar to TFC of initial SES. Thus seismoacoustic pressure from SES causes a refractive index changing. This in turn causes the C-OTDR- speckles dramatically change. This change forms a useful signal eventually. This change forms a useful signal eventually. After that, during Feature Extraction Stage, we retrieve the desired features of the useful signal. These features are used for solution of detection and classification tasks. A simplified scheme of the C-OTDR-system is shown on Fig. 1.

In addition to the C-OTDR-sensor, class DAS includes several types of sensors, which use different optical effects. C-OTDR-sensor uses Rayleigh backscatter. The Brillouin fiber sensors use Brillouin Scattering. Both of these sensors belong to a DAS class. In practice, there are always sites of the object perimeter, where it is impossible to use the optical fiber or where the fiber-optic based technologies are non-effective. For example, part of the oil pipeline may be placed on soil with high acoustic impedance (silt, sand) therefore seismoacoustic waves of STE's will not reach to optical fiber. Thus we will not have information about these STE's. For detection and classification of these STE's we must use sensors of another physical type (modality), for example, far CCTV or sensors to monitor gamma-ray background. Another case is connected with situation, when we need to control a development of karst processes near monitored objects. Here, methods with optical fiber usage are ineffective, and it is better to use net of inclinometers. Thus we have objective situation when the monitoring system must to be multimodal, at the same

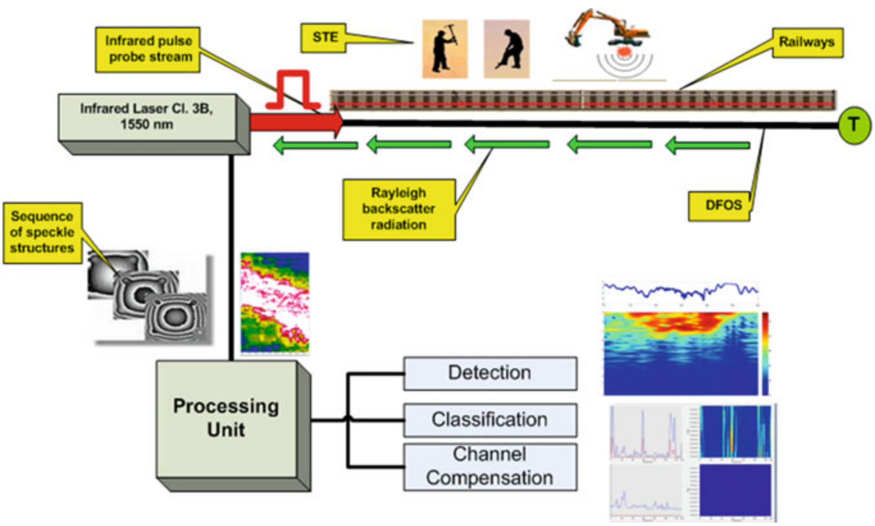


**Fig. 1** Simplified scheme of C-OTDR monitoring system

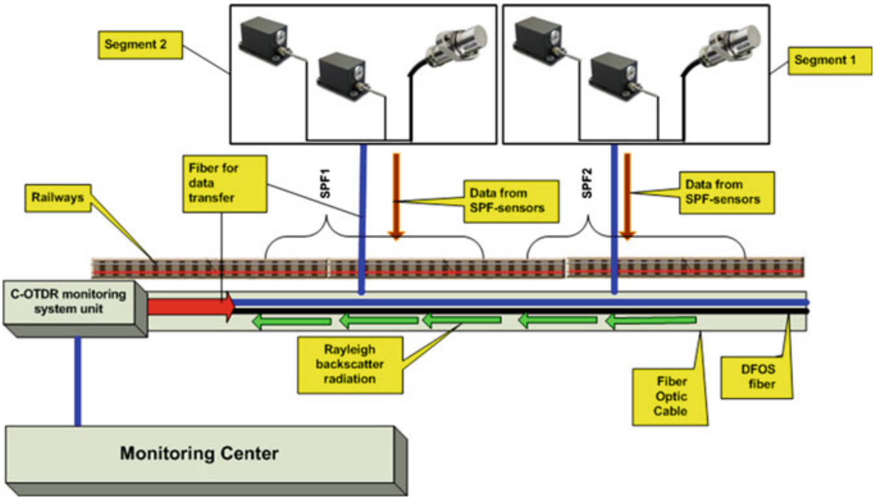


**Fig. 2** Simplified scheme of a heterogeneous multimodal monitoring system

time architecture of monitoring system must be heterogeneous to answer real monitoring challenges. On the design stage of monitoring system, we must distinguish between object perimeter fragments that need special supervision or certain key features. For example, when designing a monitoring system intended to monitor railroad tracks, we should focus on fragments of object perimeter that are close to the places of probable displacement of rocky ground. We will denote such fragments by a SPF. The architecture of heterogeneous multimodal monitoring system consists of subnets of various types point-sensors. These subnets we will call “segments”. Each segment includes set of point-sensor with various physical natures’ (geophones, gamma-ray sensors, camcorders, inclinometers etc.). These sensors are placed around respective SPFs and we will name these sensors as SPF-sensors. The Fig. 2 shows the simplified scheme of a heterogeneous multimodal monitoring system (HMM-system).

Here fiber-optic cable is used as DAS (one or two fibers) and also for data transfer (rest fibers). Of course, this cable should be buried in a vicinity of monitored object. The HMM-systems are multichannel by definition and for system of such kind the term “channel” is very important. This common term implies two meanings: DAS-channel and Information channel for getting data from SPF-sensors. The DAS-channel is virtual one. De facto it is a small part of DFOS, data from which corresponds to seismoacoustic field in vicinity of it. The size of this part (DAS-channel width) is determined by the length of the probe pulse. In practice the DAS-channel width is about 2–10 m and namely this parameter determines a spatial resolution ability of DAS-systems. In case of SPF-sensors, the “channel” is simple physical information channel (fiber-optical, twisted pair etc.), and this term has clearly physical meaning. On level of data processing, each of these channel types viewed as tool for receiving data from particular point of the object. At the same time, each of those tools has individual indicators of quality, the rate of measurement, and accuracy. All of those indicators we take into account for solution of tasks “D”, “L”, “C” and “S”.

### 3.2 Information Channels of Heterogeneous Multimodal Monitoring System

Indexes of channels HMM-system in conjunction form a set Z = {1, 2, …}. In every channel $j \in \mathbf{Z}$, $S_j(t)$ is a measurement of the seismoacoustic field as function of time. We will consider two general types of sensors: point-sensors and DAS. In case of point-sensor, each channel $j \in \mathbf{Z}$ is characterized by its coordinates (it is coordinates of point-sensor). In case of DAS, every channel represents the sector of DFOS of length N meters. Coordinates of every DAS-channel $j \in \mathbf{Z}$ are fully defined by the coordinates of its beginning $b(j)$ and ending $e(t)$ points. The 2-tuple $(b(j), e(j))$ is called boundaries (start and end) of the channel $j$. If two channels match at least one of the boundaries, these channels are called adjacent. A group of adjacent channels (GAC) is the set of channels, each of which is adjacent to at least one of the GAC. The boundaries of all channels are given and form the tuple $\mathbf{X}(\mathbf{Z}) = \langle x_1, x_2, \ldots \rangle$. For jth channel we have $(b(j), e(j)) = (\langle \mathbf{X}(\mathbf{Z}) \rangle_j, \langle \mathbf{X}(\mathbf{Z}) \rangle_{j+1})$, here $\langle \mathbf{X} \rangle_j$ is jth component of the tuple $\mathbf{X}(\mathbf{Z})$. STE’s leaves traces in seismoacoustic field, and STE’s are the cause of SES appearance in this case. Next, seismoacoustic wave propagating from SES, reaches a certain GAC with delays proportional to a distance from the location of the SES to a particular channel of GAC. The specific composition of GAC determined by the location SES, its energetic power, distance of up to FOS, as well as the parameters of the wave propagation medium. We call the GAC, which turned out under the influence by the seismoacoustic waves from SES, the detecting GAC (DGAC). Observations are made at successive times, which form a set $T = \{t_1, t_2, \ldots\}$, $\forall i > 0 : t_{i+1} - t_i = \Delta t > 0$. Thus, the observations are form the following sets $\mathbf{S}_j = \{S_j(t) | t \in T\}$, $j \in DGAC$. All channel and inter-channel statistics are defined on the intervals of duration $\Delta$. Each of those intervals contains z of the discrete observations.

## 4 The Guaranteed Detection of the Spatial-Time Events in Multi-channel Monitoring Systems

In this section we describe two approaches to guaranteed detection of STE in multi-channel monitoring systems. First of them is based on simultaneously data processing in several channels. This approach can be useful for DAS-sensors, as well as for point-sensors. Second approach is based on separately data processing in every channel. This method is useful for both types of sensor too, but this method requires less computational resources.

## *4.1 The Robust Guaranteed Detection of the Spatial-Time Events with Usage of Simultaneously Data Processing in Several Channels*

For convenience, we will describe suggested method on example of DAS monitoring system (DAS-MS). In DAS-MS, STE's regarded as SES's. Specificity of the modern DAS monitoring systems is such that any two channels are statistically independent only if no SES, the elastic vibration from which affects the speckle patterns of these channels simultaneously. If such the SES exists, those channels are become statistically dependent. In this case we can speak about a group of SES, seismoacoustic waves from which will affect the FOS channels simultaneously and compositionally. Obviously, the observations of any two channels of the DGAC are statistically dependent. We call the area the sensitivity of the monitoring system the area Ω which situated in vicinity of FOS and with the appearance inside which one or a group of SES, the observations $\mathbf{S}_j, j \in DGAC$, of the appropriate DGAC will be abruptly change their statistical characteristics. In other words, observations $\mathbf{S}_j, j \in DGAC$ will are mutually dependent after appearance inside Ω one or a group of SES.

### 4.1.1 Requirements for the Decision Procedure

Let us denote

- $\tau$ is the moment of abrupt change of the observations distributions, which happened because of appearance the SES in Ω; actually, $\tau$ is a point of appearance the signals from the SES in DGAC or **change-point moment**;
- hypothesis $H_0$: in the region Ω do not SES (background model);
- hypothesis $H_1$: in the region Ω is at least one SES (signaling model);
- $\alpha \in ]0,1[$is a predetermined upper bound for the probability of making type I errors;
- $\beta \in ]0,1[$ is a predetermined upper bound for the probability of making type II errors;
- $\mathbf{\Delta}(t) = [t - z, t]$ is the interval for calculation of the speckle-structures statistical characteristics (speckle-metrics), where z is the number of the discrete observations inside of the interval $\mathbf{\Delta}(t)$; during monitoring the interval $\mathbf{\Delta}(t)$ is shifted by an amount $\Delta t$ along the time axis T;

- $$\widetilde{S}_j(t, t+z) = \{S_j(t), S_j(t+1), \ldots, S_j(t+z)\} \subseteq \mathbf{S}_j;$$

- $$\overline{\widetilde{S}}_j(t_1, t_2) = \sum_{t=t_1}^{t_2} S_j(t)(t_2 - t_1)^{-1}; \overline{\overline{S}}_j(t_1, t_2) = \sum_{t=t_1}^{t_2} \left(S_j(t) - \overline{\widetilde{S}}_j(t_1, t_2)\right)^2;$$

- $$\overline{\overline{\mathbf{S}}}_{ji}(t_1, z, \delta) = \overline{\overline{S}}_j(t_1, t_1 + z)\overline{\overline{S}}_i(t_1 + \delta, t_1 + z + \delta);$$

- $$U(z|t, t_1, j) = \left(\widetilde{S}_j(t) - \overline{\widetilde{S}}_j(t_1, t_1 + z)\right);$$

- $$r^{(i,j)}(t_1, t_1 + z|\delta) = \sum_{t=t_1}^{t_1+z} U(z|t, t_1, j)U(z|t+\delta, t_1+\delta, j)\left(\overline{\overline{\mathbf{S}}}_{ji}(t_1, z, \delta)\right)^{-0.5};$$

- $\boldsymbol{\Sigma}(\mathbf{Z}) = \bigcup_{j \in DGAC} \mathbf{S}_j$; $\rho(t|\boldsymbol{\Sigma}(\mathbf{Z}), \boldsymbol{\Delta}(t)) \subseteq R^1$ is some stochastic function, which we will call the **signaling function**; this function is defined on the interval $\boldsymbol{\Delta}(t)$ and depends on the $\boldsymbol{\Sigma}(\mathbf{Z})$ so that: $\mathbf{E}(\rho(t|\cdot)|H_0) = 0, \mathbf{E}(\rho(t|\cdot)|H_1) > 0, \mathbf{E}(\rho^2(t|\cdot)|H_0) < \infty$.

Watching $\mathbf{S}_j = \{S_j(t)|t \in T\}, j \in \mathbf{Z}$, need to define a decision function $W(t, z, \rho, \alpha, \beta) \in \{0, 1\}$, that depends on the $\rho(\cdot), \boldsymbol{\Delta}(t) = [t - z, t]$, and on the parameters $\alpha, \beta$ such that

- $$\mathrm{P}[W(t, z, \rho, \alpha, \beta) = 1|\tau \notin [t - z, t]] \leq \alpha,$$

- $$\mathrm{P}[W(t, z, \rho, \alpha, \beta) = 0|\tau \in [t - z, t]] \leq \beta.$$

Thus, it has been tasked interval estimation of the change-point τ (τ is the moment of the appearance the SES in Ω). The solution should guarantee the predetermined upper bounds for the probabilities of making type I (α) and type II (β) errors. In this formulation, the problem of detection SES reduces to problem of interval estimation of **change-point** τ.

### 4.1.2 Selecting a Robust Signaling Function $\rho$

By definition the signaling function $\rho(t|\boldsymbol{\Sigma}(\mathbf{Z}),\boldsymbol{\Delta}(t))$ abruptly changes its average value (towards increase) at the moment τ. It's desirable to the probability distribution of the $\rho$ had been robust to outliers in the observations $\boldsymbol{\Sigma}(\mathbf{Z})$. By the condition of the problem statement, vectors, $\widetilde{S}_i(t+\delta, t+z+\delta)$ satisfy the conditions of Theorem 8.1 [4], p. 204, if $t+z+\delta<\tau$. Following this theorem, $\forall_{i,j,\delta}\{\mathbf{E}(r^{(i,j)}(t,t+z|\delta))=0, \mathbf{E}(r^{(i,j)}(t,t+z|\delta))^2=(z-1)^{-1}\}$. As the problem statement dictates we can use the following function as a signaling one:

$$\rho(t|\boldsymbol{\Sigma}(\mathbf{Z}),\boldsymbol{\Delta}(t)) = \sup_{i,j\in DGAC}\left[\sup_{\delta}\left(r^{(i,j)}(t,t+z|\delta)\right)\right]. \tag{4.1}$$

However, this function is not robust to the statistical anomalies of observations. The robust estimates of the correlation coefficient were considered in [3–7]. In Sect. 8.3 [5], a powerful approach was suggested to obtain the robust estimates. Following [5], when calculating $r^{(i,j)}(t,t+z|\delta)$, instead $\widetilde{S}_j(\cdot), \widetilde{S}_i(\cdot)$ uses some $\mathbf{u}\left(\widetilde{S}_j(\cdot)\right), \mathbf{v}\left(\widetilde{S}_i(\cdot)\right)$, which were calculated from $\widetilde{S}_j(\cdot), \widetilde{S}_i(\cdot)$ respectively, according to next five rules:

1. $\mathbf{u} = \Psi\left(\widetilde{S}_j(\cdot)\right), \mathbf{v} = \Xi\left(\widetilde{S}_i(\cdot)\right)$;
2. $\Psi, \Xi$ commute with permutations of the components of $\widetilde{S}_j(\cdot), \mathbf{u}$ and of $\widetilde{S}_i(\cdot), \mathbf{v}$;
3. $\Psi, \Xi$ preserve a monotone ordering of the components of $\widetilde{S}_j(\cdot), \widetilde{S}_i(\cdot)$;
4. $\Psi = \Xi$;
5. $\forall a>0, \forall b, \exists a_1>0, \forall b_1, \forall \mathbf{x}\Psi(a\mathbf{x}+b) = a_1\Psi(\mathbf{x})+b_1$.

In the following two examples (from Sect. 8.3 [5]) all five requirements hold:

- the classical Spearman rank correlation between $\widetilde{S}_j(\cdot)$ and $\widetilde{S}_i(\cdot)$;
- the quadrant correlation between $\widetilde{S}_j(\cdot)$ and $\widetilde{S}_i(\cdot)$.

If the $r^{(i,j)}(t,t+z|\delta)$ was calculated by means of the classical Spearman rank, we will denote this as $r_{sr}^{(i,j)}(t,t+z|\delta)$. And if the $r^{(i,j)}(t,t+z|\delta)$ was calculated using the quadrant correlation, we will use the following notation $r_{qc}^{(i,j)}(t,t+z|\delta)$. Both of them $r_{sr}^{(i,j)}(t,t+z|\delta)$ and $r_{qc}^{(i,j)}(t,t+z|\delta)$ are robust to the statistical anomalies of observations. Therefore, the corresponding signaling functions

$$\rho_{sr}(t|\boldsymbol{\Sigma}(\mathbf{Z}),\boldsymbol{\Delta}(t)) = \sup_{i,j\in DGAC}\left[\sup_{\delta}\left(r_{sr}^{(i,j)}(t,t+z|\delta)\right)\right]$$

and

$$\rho_{qc}(t|\boldsymbol{\Sigma}(\mathbf{Z}), \boldsymbol{\Delta}(t)) = \sup_{i,j \in DGAC}\left[\sup_{\delta}\left(r_{qc}^{(i,j)}(t, t+z|\delta)\right)\right]$$

are robust too. It easy to see:

$$\forall t < \tau : [\mathbf{E}\rho_{sr}(t|\cdot) = 0, \mathbf{E}\rho_{sr}^2(t|\cdot) = 1/(z-1)] \tag{4.2}$$

$$\forall t < \tau : \left[\mathbf{E}\rho_{qc}(t|\cdot) = 0, \mathbf{E}\rho_{qc}^2(t|\cdot) = 1/(z-1)\right].$$

Thus, functions $\rho_{sr}$ and $\rho_{qc}$ may be used as the robust signaling functions (RSF). The RSF we will denote as s $\rho_{rb} \in \{\rho_{sr}, \rho_{qc}\}$.

### 4.1.3 Guaranteed Detection Method of the SES

As it follows from (4.2), until the moment $\tau$ the expectation of the RSF is zero. Under influence of elastic vibrations from SAE, expectation of the RSF abruptly changes towards increase, because the observations at once several channels of DGAC become statistically dependent. In other words, at the moment τ the model of RSF will get change-point of its probabilistic properties compared with the background model $H_0$. Let us describe the method for interval estimation of the moment $\tau$.

*Remark 1* If $W(t, z, \rho, \alpha, \beta) = 1$ the $[t-z, t]$ will be confidence interval for moment τ. In the case of realization the event $W(t, z, \rho, \alpha, \beta) = 1$ decision will be taken that $\tau \in [t-z, t]$. Essentially—it is a fact of detection SAE. And it is guaranteed the predetermined upper bounds for the probabilities of making type I (α) and type II (β) errors.

Properties of the proposed method are described in the following theorem:

**Theorem 4.1** *Let*

1. $\exists C > 1 : \mathbf{Var}(\rho_{rb}(t|\boldsymbol{\Sigma}(\mathbf{Z}), \boldsymbol{\Delta}(t))) \le Cz^{-1}$;
2. $\exists \theta > 0 : \inf_{t \ge \tau} \mathbf{E}\rho_{rb}(t|\boldsymbol{\Sigma}(\mathbf{Z}), \boldsymbol{\Delta}(t)) \ge \theta$;;
3. $W(t, z, \rho, \alpha, \beta) = \begin{cases} 1, & \text{if } \rho_{rb}(t|\boldsymbol{\Sigma}(\mathbf{Z}), \boldsymbol{\Delta}(t))/\theta \ge b \\ 0, & \text{if } \rho_{rb}(t|\boldsymbol{\Sigma}(\mathbf{Z}), \boldsymbol{\Delta}(t))/\theta < b. \end{cases}$

*Here* $b = \left(\frac{\beta}{\alpha C^2}\right)^{0.5}\left(1 - \left(\frac{\beta}{\alpha C^2}\right)^{0.5}\right)^{-1}$.

*Then, if* $z = 1 + \frac{C^2}{\theta^2\alpha} - \frac{2C}{\theta^2\sqrt{\alpha\beta}} + \frac{1}{\theta^2\alpha}$, *the following statements are true:*

$$\begin{aligned} &\mathrm{P}[W(t,z,\rho,\alpha,\beta) = 1|\tau \notin [t-z,t]] \le \alpha \\ &\mathrm{P}[W(t,z,\rho,\alpha,\beta) = 0|\tau \in [t-z,t]] \le \beta. \end{aligned}$$

*Remark 2* The constant $\theta$ has following sense: the algorithm will detect those SAE, for which the increment of the value $\mathbf{E}\rho_{rb}(t|\mathbf{\Sigma}(\mathbf{Z}),\mathbf{\Delta}(t))$ when $t-z \ge \tau$ will exceed the value $\theta$. Thus, parameter $\theta$ defines the sensitivities of the detection algorithm.

*Proof of Theorem 4.1* Consider the representations

$$\rho_{rb}(t|\cdot))/\theta = \begin{cases} m(t), t<\tau \\ \mathbf{E}\rho_{rb}(t|\cdot)/\theta + m'(t), t-z \ge \tau \end{cases}$$

In view of (4.2) we have:

$$\mathbf{E}m(t) = 0, \mathbf{E}m^2(t) = 1/(\theta^2(z-1)). \tag{4.3}$$

Using Chebyshev's inequality, we write:

$$\begin{aligned} &\mathrm{P}[W(t,z,\rho,\alpha,\beta) = 1|\tau \notin [t-z,t]] = \\ &\mathrm{P}[\rho_{rb}(t|\cdot)/\theta > b|\tau \notin [t-z,t]] \le \\ &\mathrm{P}[|m(t)| > b] \le (\theta^2(z-1)b^2)^{-1}. \end{aligned} \tag{4.4}$$

When $\tau > t-z$ from condition 2 we have $\mathbf{E}\rho_{rb}(t|\mathbf{\Sigma}(\mathbf{Z}),\mathbf{\Delta}(t))/\theta \ge 1$. Therefore, taking into account the first condition of the theorem, we can write:

$$\begin{aligned} &\mathrm{P}[W(t,z,\rho,\alpha,\beta) = 0|\tau \in [t-z,t]] = \\ &\mathrm{P}[\mathbf{E}\rho_{rb}(t|\cdot)/\theta + m'(t) < b|\tau \in [t-z,t]] \le \\ &\mathrm{P}[|\mathbf{E}\rho_{rb}(t|\cdot)/\theta| - |m'(t)| < b|\tau \in [t-z,t]] \le \\ &\mathrm{P}[|m'(t)| > |\mathbf{E}\rho_{rb}(t|\cdot)/\theta| - b] \le \\ &\mathrm{P}[|m'(t)| > 1-b] \le C^2/(z\theta^2(1-b)^2) \le \\ &C^2/((z-1)\theta^2(1-b)^2). \end{aligned} \tag{4.5}$$

Substituting in (4.4) and (4.5) the values of z and b, as defined in the condition of the theorem immediately confirm the truths of the allegations are proved. The theorem is proved. ■

The approach described in this report is used for the detection of SES in real C-OTDR monitoring system (C-OTDR-MS). Parameters of the C-OTDR-MS: the probe pulse duration: 50–150 ns; frequency sensing: 2–8 kHz; the probe signal power—15 mW; laser wavelength: 1550 nm. Table 1 contains results of SES's detection. Here «Distance» is an average distance at which the given class of SES was detected, $P_I$—is detection error of the type I; $P_{II}$—error of the type II. Parameters of the detection system were such: z = 25, $\theta = 0.2, \alpha = 0.1, \beta = 0.1$. The parameter C was estimated experimentally: C $\sim$ 1.3. Data are presented for

**Table 1** The practical detection results

| Type of SES | Distance (m) | $P_I$ | $P_{II}$ |
|---|---|---|---|
| "hand digging the soil" | 10 | 0.09 | 0.08 |
| "chiselling ground scrap" | 5 | 0.1 | 0.1 |
| "walking man" | 10 | 0.07 | 0.09 |
| "running man" | 15 | 0.09 | 0.08 |
| "passenger car" | 25 | 0.06 | 0.1 |
| "truck" | 35 | 0.07 | 0.09 |
| "heavy equipment excavator" | 50 | 0.02 | 0.01 |
| "easy excavation equipment" | 40 | 0.03 | 0.02 |

rocks cemented soil. The results in Table 1 show sufficiently high practical effectiveness of the described SES detection system. We have to note this method is very demanding to computational resources; therefore it may only be used in systems with a small number of channels.

## 4.2 Method of Adaptive Sequential Real-Time Detection of Spatial-Time Events in Multichannel Monitoring Systems

In case of super-extended object monitoring, the conditions of observation are dramatically different at different times and different places. These circumstances strongly influence sensors systems. The influence implies an increase in Type I and Type II errors. While noise level may dramatically be different in various time intervals for one and the same channel, the industrial noise power and its spectral characteristics as a rule are stable for extended periods of time (no less than a few minutes or sometimes even hours). Unlike the industrial noises, targeted signals have high power and short duration (no more than a few minutes). So, targeted signals have a shorter stability period with respect to stability period of noises. Using this assumption, we can build an adaptive real-time detector which will guarantee prescribed level for Type I and Type II errors. This approach will be described in this section on an example of C-OTDR-MS with a high number of channels (more than 20,000). Suggested method contains two phases: (a) phase adaptation to background noises, and (b) phase of SES's detection. Both phases are based on a sequential analysis approach. Let us denote: $\tau_j$ is random moment time. So, $\tau_j$ is the moment of abrupt change of the observations distributions in jth channel; this change happened due signal appearance; actually, $\tau_j$ is the change-point moment [8, 9] of observation distributions; $t_0$ is time of observation start; $h$ is the sample size for initial adaptation to noise; $P_c$—confidence coefficient, $0 < P_c < 1; \Delta(h) = 2((1 - P_c)h)^{-0.5}$; hypothesis $H_0$: in channel do not signal (background model); hypothesis $H_1$: in channel is signal (signaling model); $\delta$—desired size of confidence interval for background model; $\alpha \in (0,1)$ is a predetermined upper bound for the probability of making type I errors; $\beta \in (0,1)$—is a predetermined upper bound for the probability of making type II errors.

### 4.2.1 SES's Detection Problem Set and Requirements for the Decision Procedure

For each channel $j \in \mathbf{Z}$ observations are described by following expressions:

$$\forall t < \tau_j, t \in \Delta : S_j(t) = \theta_j + \sigma_j(t)\varsigma_j(t)$$

$$\forall t \geq \tau_j, t \in \Delta : S_j(t) = \theta_j + \sigma_j(t)\varsigma_j(t) + \theta_{s,j}(t) + \pi_j(t)\xi_j(t).$$

Here

- $\{\varsigma_j(t)\}, \{\xi_{s,j}(t)\}$ are mutually independent random variables, $\mathbf{E}\varsigma_j(t) = 0, \mathbf{E}\varsigma_j^2(t) = 1, \mathbf{E}\xi_{s,j}(t) = 0, \mathbf{E}\xi_j^2(t) = 1, \sigma_j \leq L_N, \pi_j \leq L_S$; the constants $L_N, L_s$ are given; noise parameters $\{\theta_j\}$ are priori unknown.
- $\underset{i \neq j}{\forall}\, \theta_i \neq \theta_j, \Xi_{s,j}(t) = \theta_{s,j}(t) + \pi_j(t)\xi_j(t)$ is equation of target signal in $j$th channel, $\theta_{s,j}(t) > 0$.

The research objective is to build a **SES's detection procedure**, which will guarantee the prescribed level for Type I (α) and Type II (β) errors. In solving this problem for each channel we can use observations of this channel only. So, we do not have a possibility to use cross-channel information, in contrast to method of 4.1.3. This is due presence of huge number of channels (more than 20,000), data from which we have to process in real time.

### 4.2.2 Method of Adaptive Sequential Real-Time SES's Detection

During adaptation phase of background model parameters are estimated. In frame of suggested conception we interest in parameters $\{\theta_j\}$ estimation. We need to know the one-sided confidence upper bounds for parameters $\{\theta_j\}$ with given confidence coefficient $P_c$. For solution of this task we will use the sequential analysis. Let us consider the following simple statistic:

$$\bar{\bar{\theta}}_j(t_0, h) = \sum_{p=t_0}^{t_0+h} S_j(p)/(L_N h) + ((1 - P_c)h)^{-0.5}.$$

The $\bar{\bar{\theta}}_j(t, h)$ is non-parametric confidence upper bound for $\theta_j$, and it is easy to see that $\mathbf{P}(\theta_j \leq \bar{\bar{\theta}}_j(t_0, h)) \geq P_c$ and $\underset{j}{\forall} P\left(\lim_{h \to \infty} \bar{\bar{\theta}}_j(t_0, h) \to \theta_j\right) = 1$. So, interval

$(t_0, t_0+h)$ is called initial interval adaptation to noise (IIAN); calculation of $\overline{\overline{\theta}}_j(t,h)$ we will call as "adaptation to noise" (AN-procedure). Let us consider following cycle statistics:

$$Y_j(t|h,H) = (H(\Delta(h)+\varepsilon))^{-1}\left(\sum_{k=t-z}^{t-1}\frac{S_j(k)}{L_N^2+L_S^2}\right) - \frac{\overline{\overline{\theta}}_j(t_0,h)}{\Delta(h)+\varepsilon} + \frac{\alpha' S_j(t)}{(\Delta(h)+\varepsilon)H}.$$

$$z = \inf\left\{t \geq t_0 + h | t \geq H\left(L_N^2+L_S^2\right)\right\}, \alpha' = H - (z-1)/\left(L_N^2+L_S^2\right), \varepsilon > 0$$

Statistics $Y_j(t|h,H)$ are defined on the sequence of the intervals:

$$U(z,t_0) = \{u(t_i,z)|i \geq 1, u(t_i,z) = (t_i, t_i+z+1), t_i = t_{i-1}+z+1, t_i \geq t_0\}.$$

Those cycle statistics $Y_j(t|h,H)$ will be used for guarantee detection of signals by reducing the task of detection signals to the task of the moment $\tau$ interval estimation. As confidence interval we will consider any interval $u(t_i,z)$ from sequence $U(z,t_0)$. Once $Y_j(t_i+z+1|h,H)$ is calculated, we have to decide what is right: $\tau \in u(t_i,z)$ or $\tau \notin u(t_i,z)$. Simply put, the accuracy of moment $\tau$ estimation is z. The conditions, which guarantee a prescribed reliability of the algorithm, are determined by the following

**Theorem 4.2** *Let*

1. $1-P_c < \alpha, 1-P_c < \beta.$
2. $\underset{j}{\forall} \exists \varepsilon > 0 : \underset{t \geq \tau}{Inf}\ \theta_{s,j}(t) \geq 2\Delta(h)+\varepsilon.$
3. $H = P_c\left[(\beta-1+P_c)(1-b)^2(\Delta(h)+\varepsilon)^2\right]^{-1}$, *where* $b = \left(\frac{c\mathbf{m}+1}{c+1}\right), c = \left(\frac{\alpha-1+P_c}{\beta-1+P_c}\right)^{0.5}$, $\mathbf{m} = \frac{\Delta(h)}{\Delta(h)+\varepsilon}.$

*In this case, if the decision rule will be defined by the following way*

$$R(b) = \begin{cases} \text{if } Y_j(t|h,H) \geq b \text{ then } H_1 \text{ is true in jth channel} \\ \text{if } Y_j(t|h,H) < \text{b then } H_0 \text{ is true in jth channel} \end{cases},$$

*then next inequalities will be true for prescribed $\alpha$ u $\beta$:*

1. $\mathbf{P}\left(Y_j(t_i+z+1|h,H) < b|H_1 : \tau \in u(t_i,z)\right) \leq \beta$
2. $\mathbf{P}\left(Y_j(t_i+z+1|h,H) \geq b|H_0 : \tau \notin u(t_i,z)\right) \leq \alpha.$

The proving of this theorem is similar to proving of Theorem 4.1. The approach described in this section is used for the detection of SES's in a real C-OTDR-MS, which has been described in 4.1.3. Table 1 contains the results of detection of SES's. Here «Distance» is an average distance at which the given class of SES was detected, $P_I$—is a detection error of type I; $P_{II}$—an error of type II; "Type of Noise" is the type of the background industrial noise (there are two types: "noise of water

Table 2 The practical detection results

| Type of SES | Distance (m) | $P_I$ | $P_{II}$ | Type of noise |
|---|---|---|---|---|
| "hand digging the soil" | 10 | 0.15 | 0.09 | Type 1 |
| "chiseling ground scrap" | 5 | 0.18 | 0.09 | Type 2 |
| "walking man" | 10 | 0.19 | 0.09 | Type 2 |
| "cutting frozen soil" | 15 | 0.14 | 0.1 | Type 1 |
| "train" | 20 | 0.0 | 0.0 | Type 2 |

drain" (type 1), and "noise from the diesel generator" (type 2). Parameters of the detection system were as follows: $h$ = 200 (since update rate of models is 20 Hz, the adaptation interval length is 10 s), $\alpha = 0.2$, $\beta = 0.1$. Table 2 shows sufficiently high practical effectiveness of the described SES detection system.

## 5 Classifications of Spatial-Time Events

In practice, STE leaves traces in different types of physical fields. Therefore, for STE classification we can use sensors of different types, each of them correspond to respective physical field. Every sensor type implies usage of respective features, which describe the STE, and which can be used for classification. We will not discuss methods of feature selection; we assume that for each sensor type the respective feature set has already been formed. For example, CCTV-system design took into account fact that shape and color features are more efficient in contrast with dynamics features [10]. The shape/color characteristics: Scale Invariant Feature Transform (SIFT) [11], Color SIFT [12], Histogram of Oriented Gradient (HOG) [13], and other. The dynamics features: Space-Time Interest Points (STIP) [14], Dense Trajectories [15]. In case of C-OTDR monitoring system can use the tandem LFCC (Linear-Frequency Spaced Filterbank Cepstrum Coefficients)-GMM (Gaussian mixture model) is the most effective feature for the SES classification [16]. LFCC-GMM-vectors with dimension 1024 were used as C-OTDR features. Here LFCC's are defined for speckle-structures of particular C-OTDR channels.

In this section we consider methods of information fusion, which allow effectively taking into account the heterogeneous data of different sources in process of STE classification.

### 5.1 *The Multimodal Algorithm of STE Classification*

In order to provide functionality of the multimodal monitoring system different subsystems were trained together, as group of independent classifiers on the same labeled data. For example, for case of bimodal monitoring system [16] the CCTV and C-OTDR subsystems were trained together with good result. Let us denote $\varphi_j$—$j$th feature; $K$-number of features; m—number of STE classes; indexes of those classes form a set $\mathbf{I}$; $\mathbf{x}(t)$ is a generalized super-vector of a channel measurements; super-vector $\mathbf{x}(t)$ combines data of all sensors at the time moment $t$, $\mathbf{x}(t) = (x_1(t), x_2(t), \ldots, x_K(t)), \forall x_j(t) \in R^{d_j}, \mathbf{x}(t) \in R^D, D = \prod_{j=1}^K d_j, x_j(t)$ is data of $j$th sensor at the time moment $t$, $R^{d_j}$ is $d_j$-dimensional feature space of $j$th feature. It's obvious that each feature $\varphi_j$ is a function of argument $x_j(t)$; so we can write $\varphi_j\left(x_j(t)\right)$. On training stage, each class represents with N samples. $\left\{\left(\varphi_j\left(x_j(t_l)\right), y_l\right) | l = 1, \ldots, N\right\}$—training sample set for jth feature, $t_l$—time of getting $l$-sample. Here and further, $y_l \in \mathbf{I}$. Following the conclusions of [17] as algorithm of STE classification was used by a so called multiclass ν-LPBoost [18], built as a linear convex hull of Lipschitz classifiers. This method steadily works even at a small training sample size [17]. As the Lipschitz classifiers have used conventional SVM (Support Vector Machine) [19]. We denote $f_{j,i}(\cdot|\alpha_{j,i}, b_{j,i}) \equiv f_{j,i}(\cdot)$—SVM classifier, which corresponds to $\varphi_j$ feature ($j$th feature space), and to $i$th STE class ($i \in \mathbf{I}$); $\left(\alpha_{j,i}, b_{j,i}\right)$—parameters of $j$th SVM classifier, those parameters are subject to setting up on training stage. So, we have the set of classifiers $\left\{f_{j,i}(\cdot|\alpha_{j,i}, b_{j,i}) | i \in \mathbf{I}, j = 1, \ldots K\right\}$.

To solve the multiclass classification SES problem those SVM-classifiers were trained by well-known scheme **one-against-all** (for according feature spaces). According to the concept **one-against-all** every class $i$ is separated from the other classes by use the corresponding classifier $f_{j,i}(\cdot|\alpha_{j,i}, b_{j,i})$ in the respective feature space. All these SVM-classifiers $f_{j,i}(\cdot|\alpha_{j,i}, b_{j,i})$ are built based on the product Bhattacharya kernels [20]. Optimization of the classifiers parameters $\left(\alpha_{j,i}, b_{j,i}\right)$ was made by use of usual cross-validation (CV) scheme.

A multimodal discriminant function of ν-LPBoost-classifier [17], has the following simple form:

$$F(\mathbf{x}(t)) = Arg \max_{i \in \mathbf{I}} \left( \sum_{j=1}^K \beta_j f_{j,i}(\varphi_j(x_j(t_l)) | \alpha_{j,i}, b_{j,i}) \right).$$

The training phase comes down to an optimal choice of parameters $\left\{\beta_j\right\}$. This choice is performed by using standard optimization method (**linear programming**) according to the following scheme:

$\min\limits_{\beta,\xi,\rho} \left( -\rho + \frac{1}{\nu N} \left( \sum\limits_{k=1}^N \xi_k \right) \right)$, under the condition:

$$y_k \sum_{j=1}^K \beta_j f_{j,y_k}(\varphi_j(x_j(t_l)) | \cdot) - \arg \max_{y_p \neq y_k} \left( \sum_{j=1}^K \beta_j f_{j,y_p}(\varphi_j(x_j(t_l)) | \cdot) \right)$$
$$+ \cdots + \xi_k \geq \rho, k = 1, \ldots N, \sum_{j=1}^K \beta_j = 1, \beta_j \geq 0, j = 1, \ldots K.$$

Here $\xi$—slack variables, $\nu$—regularization constant, which is chosen using CV. The training was carried out with the advice of [17]. Thus, the two stage scheme was used to avoid the biased estimates. In [17] this scheme is described in detail.

## 5.2 The STE Classification Algorithm Application Results

The multimodal algorithm of STE classification showed good performance and stability when used in a bimodal surveillance system [16]. This system is using measurements of two types of physical fields: seismoacoustic and optical/infrared. In this case both the C-OTDR-MS and the Far CCTV (FCCTV) systems are used together. This bimodal surveillance system is installed at the special test area of Kazakhstan Railroads (near Astana). The C-OTDR-MS distributed fiber optic sensor (DFOS) length is 1500 m. This DFOS is buried near the railroad in depth of 50–100 cm. The quality of the FCCTV video stream is 25 fps at a resolution of 704 × 576 pixels. The system works in real time, and its goal is to monitor an operational situation in vicinity of railroad ballast prism. The targeted STE set is: “pedestrian”, “technological activities near the ballast prism”, “passenger-train”, “cargo-train”, “shunting-train”, and “animals”. As it was mentioned above, in

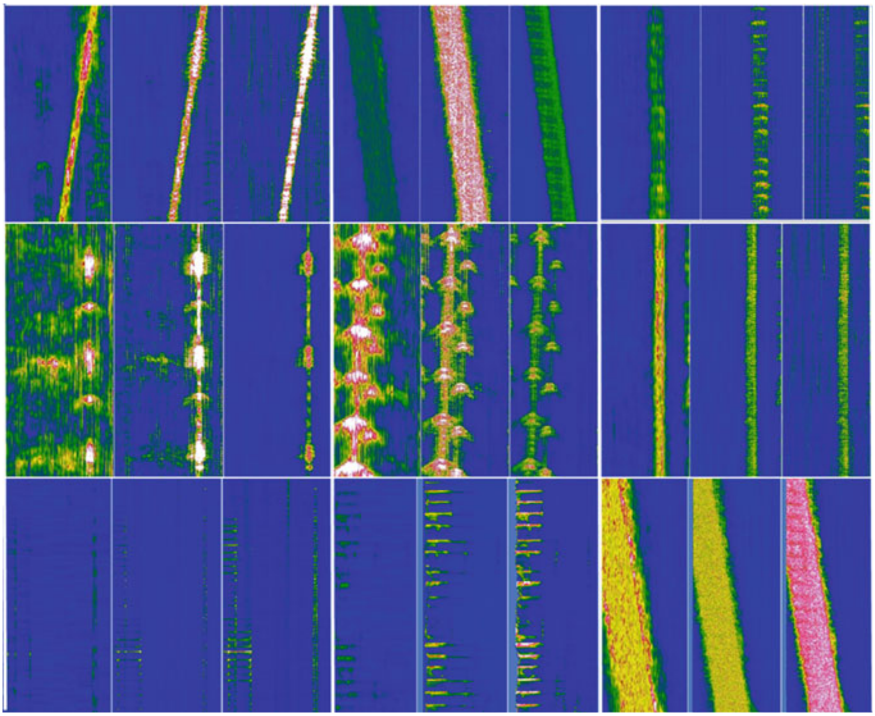

**Fig. 3** Waterfall-charts of different SES types

**Table 3** Performance Characteristics of the Bimodal Surveillance System

| Type of SES | Distance from FCCTV (m) | α | β |
|---|---|---|---|
| Technological activities | 200 | 0.02 | 0.03 |
| | 500 | 0.03 | 0.04 |
| Pedestrian | 200 | 0.07 | 0.08 |
| | 500 | 0.1 | 0.09 |
| Shunting-train | 200 | 0.06 | 0.03 |
| | 500 | 0.05 | 0.04 |
| Cargo-train | 200 | 0.01 | 0.01 |
| | 500 | 0.01 | 0.01 |
| Passenger-train | 200 | 0.01 | 0.01 |
| | 500 | 0.02 | 0.01 |

C-OTDR-MS the spatial-time events regarded as SES's. For example, the Fig. 3 represents so-called waterfall-charts of typical seismoacoustic emission sources.

Here the axis Y relates to time, the axis X relates to distance, color encodes intensity of speckle dynamics. This picture shows the waterfall-charts of different SES types in vicinity of railroad ballast prism (trains, technological activities, etc.). Waterfall-charts (9 pieces) of this picture were obtained of different parts of FOS, on three frequency bands 4–10 Hz (left part), 20–40 Hz (central part), 60–150 Hz (right part). Table 3 contains the application results of used Classification Algorithm. When testing, there were two distances from FCCTV sensors to STE: 200 and 500 meters. Symbol α denotes a value of I Type error (false reject), and symbol β—a value of II Type error (false alarm). We can assume that the application results are not bad.

## 6 Conclusions

This section contains a description of modern approaches to construction and data processing in monitoring systems of super-extended objects. These approaches were applied in real monitoring systems and have confirmed their practical effectiveness.

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