УНИВЕРСИТЕТ ИТМО
НАУЧНО-ТЕХНИЧЕСКИЙ ВЕСТНИК ИНФОРМАЦИОННЫХ ТЕХНОЛОГИЙ, МЕХАНИКИ И ОПТИКИ
май–июнь 2022 Том 22 № 3 http://ntv.ifmo.ru/
SCIENTIFIC AND TECHNICAL JOURNAL OF INFORMATION TECHNOLOGIES, MECHANICS AND OPTICS
May–June 2022 Vol. 22 No 3 http://ntv.ifmo.ru/en/
ISSN 2226-1494 (print) ISSN 2500-0373 (online)
НАУЧНО-ТЕХНИЧЕСКИЙ ВЕСТНИК УНИВЕРСИТЕТ ИТМО
ИНФОРМАЦИОННЫХ ТЕХНОЛОГИЙ, МЕХАНИКИ И ОПТИКИ

doi: 10.17586/2226-1494-2022-22-3-610-622

Monitoring of infiltration processes in hydraulic structures using distributed acoustic sensing technology

Andrey V. Timofeev[1]✉, Denis I. Groznov[2]

[1,2] EqualiZoom LLP, Nur-Sultan, 010000, Kazakhstan

[1] timofeev.andrey@gmail.com✉, https://orcid.org/0000-0001-7212-5230
[2] d.i.groznov@yandex.ru, https://orcid.org/0000-0002-7874-7118

Abstract
The article proposes a new method of monitoring the infiltration processes developing inside the body of hydraulic structures. The method is based on the use of DAS (distributed acoustic sensing) fiber-optic technology which provides high spatial continuity of hydraulic structure seismoacoustic field analysis; digital twin infiltration dynamics and efficient signal processing methods based on machine learning. As a distributed sensor of the object's seismoacoustic field, a DAS system is used the fiber-optic sensor of which is installed inside the body of the structure according to the principle of maximum coverage. The infiltration activity inside the structure body is estimated based on the analysis of an infiltration flows ensemble which are detected and classified by machine learning (ML) methods. These infiltration flows are sources of seismoacoustic emission and are therefore confidently detected by the DAS system. A digital twin of the infiltration dynamics based on the equations of mathematical physics is used as the normal basis for estimating the current state of fluid activity in the body of the structure. The risk of a structure failure under the influence of the observed infiltration flow is estimated within the framework of the proposed formal method based on the digital twin data. Based on the analysis of Data Set, consisting of real signals of infiltration processes, the high efficiency of detection and classification of this type of signals with the special ML-classifier included in the monitoring system is proved. A digital twin model of the infiltration processes dynamics in the body of a hydraulic structure is proposed. On the basis of the digital twin model, a method for estimating the risk of damage to the body of a hydraulic structure, which may occur as a result of the observed infiltration activity, is proposed. The method of controlling infiltration processes inside hydraulic structures can be used to monitor the operational condition of almost any hydraulic structures, including those in the cryolithic zone.

Keywords
DAS, infiltration process, machine learning, classification, hydraulic structures, tailings monitoring, dam monitoring, SVM, digital twin, cryolithozone, Darcy's equation

For citation: Timofeev A.V., Groznov D.I. Monitoring of infiltration processes in hydraulic structures using distributed acoustic sensing technology. *Scientific and Technical Journal of Information Technologies, Mechanics and Optics*, 2022, vol. 22, no. 3, pp. 610–622. doi: 10.17586/2226-1494-2022-22-3-610-622

УДК 004.852

Мониторинг инфильтрационных процессов в гидротехнических сооружениях с использованием распределенного акустического сенсора

Андрей Владимирович Тимофеев[1]✉, Денис Игоревич Грознов[2]

[1,2] ТОО «Эквалайзум», Астана, 010000, Казахстан

[1] timofeev.andrey@gmail.com✉, https://orcid.org/0000-0001-7212-5230
[2] d.i.groznov@yandex.ru, https://orcid.org/0000-0002-7874-7118

Аннотация
Предмет исследования. Предложен новый метод мониторинга инфильтрационных процессов, развивающихся внутри тела гидротехнических сооружений. Метод основан на использовании оптоволоконной технологии DAS (distributed acoustic sensing). Данная технология обеспечивает высокую пространственную сплошность анализа сейсмоакустического поля сооружения; цифрового двойника динамики инфильтрационных

процессов и эффективных методов обработки сигналов, основанных на машинном обучении (machine learning — ML). **Метод.** В качестве распределенного сенсора сейсмоакустического поля объекта использована DAS-система, оптоволоконный сенсор которой инсталлирован внутри тела сооружения по принципу максимального охвата. Инфильтрационная активность внутри тела сооружения оценена по совокупности обнаруженных и классифицированных методами машинного обучения инфильтрационных потоков, которые являются источниками сейсмоакустической эмиссии и поэтому уверенно детектируются DAS-системой. Цифровой двойник динамики инфильтрационных процессов, основанный на уравнениях математической физики, использован в качестве нормальной базы при оценке текущего состояния активности флюидов в теле сооружения. Риск разрушения сооружения под воздействием инфильтрационного потока оценен в рамках предложенного, формального метода, основанного на полученных данных цифрового двойника. **Основные результаты.** На основании анализа базы данных сигналов, состоящей из реальных сигналов инфильтрационных процессов, доказана высокая эффективность детекции и классификации сигналов данного типа при помощи ML-классификатора, входящего в состав системы мониторинга. Предложен цифровой двойник динамики инфильтрационных процессов в теле гидросооружения. На основе использования этой модели предложен метод оценки риска повреждения тела гидротехнического сооружения, которое может произойти в результате реализовавшейся инфильтрационной активности. **Практическая значимость.** Метод контроля инфильтрационных процессов внутри гидротехнических сооружений может быть использован для мониторинга оперативного состояния практически любых гидротехнических сооружений, в том числе в криолитозоне.

Ключевые слова

DAS, инфильтрационный процесс, машинное обучение, классификация, гидротехническое сооружение, мониторинг хвостохранилищ, мониторинг дамб, SVM, цифровой двойник, криолитозона, уравнение Дарси

Ссылка для цитирования: Тимофеев А.В., Грознов Д.И. Мониторинг инфильтрационных процессов в гидротехнических сооружениях с использованием распределенного акустического сенсора // Научно-технический вестник информационных технологий, механики и оптики. 2022. Т. 22, № 3. С. 610–622 (на англ. яз.). doi: 10.17586/2226-1494-2022-22-3-610-622

Introduction

The task of early detection of infiltration processes places intensification and formation of enlarged filtration jets (pipes) is one of the central tasks in the set of hydraulic structures monitoring [1]. The importance of intensity control of infiltration processes is due to the practice of operation of hydraulic structures which indicates that in most cases the cause of accidents is the impact of uncontrolled filtration flow in the foundation and in the body of the hydraulic structure (for example — in the body of the embankment dam). Due to climate change, the problem of timely detection of localized infiltration activity has become more important for hydraulic structures located in the cryolithic zone. For example, it is fair for numerous tailings dams. Tailings storage facility is a hydraulic structure designed to store mineral processing waste (tailings). Tailings come to the tailings pond in the form of slurry. There is a widespread opinion among hydraulic engineering specialists that a significant part of emergency situations at hydrostructures, in particular in the body of embankment dams, could be avoided if the relevant services had adequate, timely information about infiltration processes that take place in the body and in the foundation of hydrostructures [1, 2]. Of course, an adequate response to changes in the status of infiltration activity in the body of a hydraulic structure is possible only if there is an objective methodology designed to promptly assess the risk of destruction of a bulk hydraulic structure under the influence of infiltration processes occurring in its body. The present work is devoted to creating the foundation for such a methodology based on the data of continuous control of infiltration processes in the hydraulic structure body.

Filtration (infiltration) is the movement of fluids (liquid, gas, or carbonated liquid) in a porous medium [3]. In hydraulic engineering, water is considered as a fluid, and the media formed from soils, fractured rocks, concrete and other porous materials is considered as a porous medium. Since the porous structure has a fundamentally stochastic structure, hydraulic engineering considers the averaged parameters of filtration properties of the porous medium, in particular, filtration rate, filtration head, head gradient, filtration coefficient, and others. All these characteristics, to one extent or another, characterize the intensity of infiltration processes. It is assumed that during filtration the fluid moves inside the porous body, gradually filling all the space available to it: pores and soil particles. In this case, the fluid flow through any site should be equal to its real flow rate. De facto it is assumed that real fluid flow in pores of ground is replaced by some “fictitious” filtration flow of the same fluid continuously filling volumes.

Fig. 1 shows in schematic form three variants of infiltration activity state in the body of tailings dam embankment. The Fig. 1, *a* corresponds to the normal situation: infiltration process is represented in the form of local jets of small diameter which develop significantly below the level of the calculated depression curve. The Fig. 1, *b* corresponds to the situation when the intensity of the infiltration process increases to pre-critical: the thickness of jets becomes larger and their location may be above the calculated depression curve, and the actual depression curve rises. The Fig. 1, *c* illustrates a critical case: infiltration jets integrated into a large “tube” (micro-river), the dam is at critical risk. Here the depression curve has risen to a critical level; in fact, almost the entire body of the dam is covered by the infiltration process.

The existing methods of controlling infiltration processes are based on the use of point measurements which were obtained by means of piezometers placed at certain points of the body of the hydraulic structure and forming a piezometric network. However, this method has significant disadvantages, the main of which is the

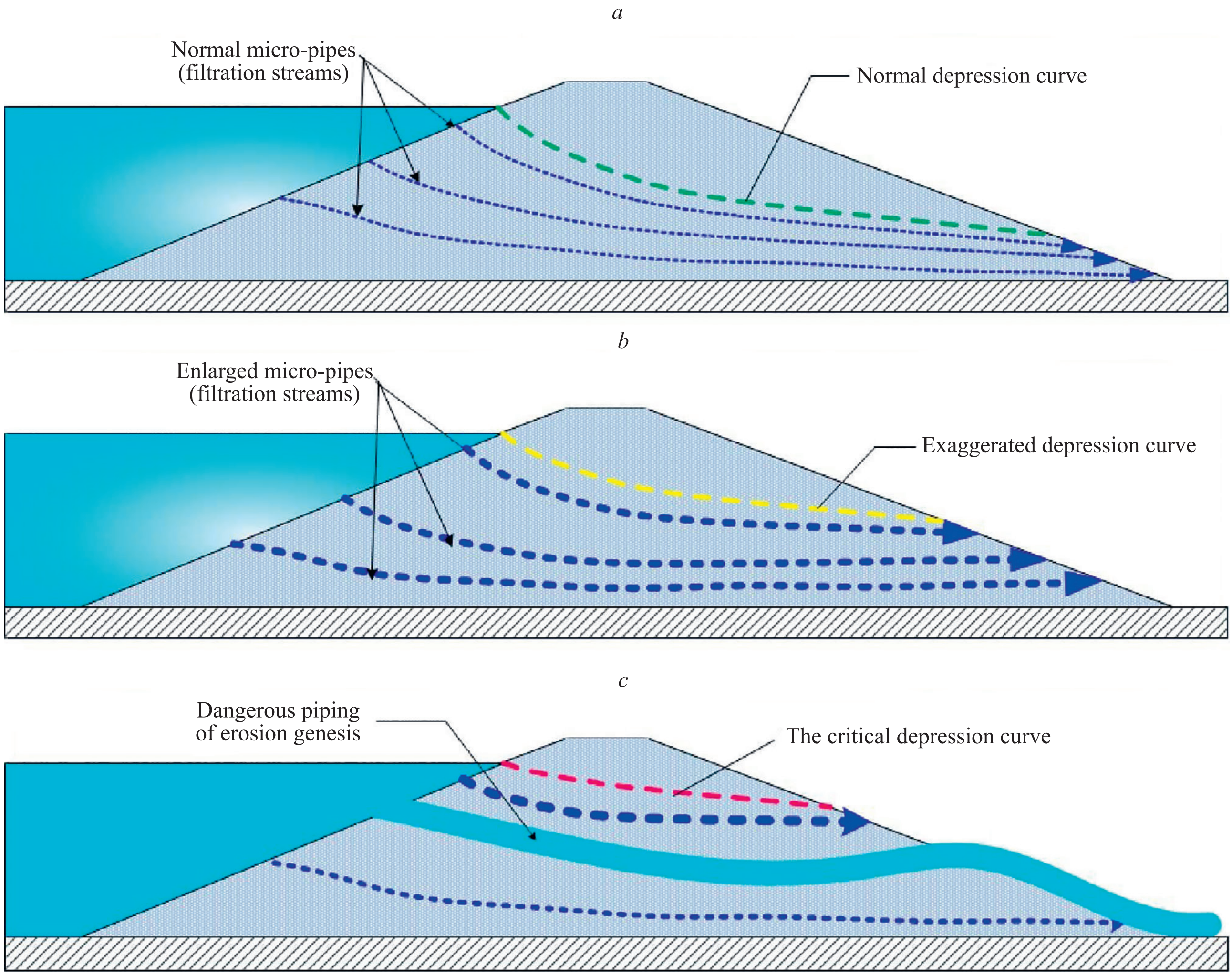

Fig. 1. Stages of infiltration process progression inside the dam body: normal situation (*a*); infiltration increasing, pre-critical situation (*b*); maximum infiltration process development, critical situation (*c*)

impossibility of controlling infiltration in areas that are not within the control zone of the piezometric network. The fact is that the practice of operation of bulk tailings dams in the cryolithic zone has shown that intensive fluid infiltration can take place in very narrow in diameter areas of the dam body. In some cases, the intensification of infiltration occurs literally in the areas of 1–2 m in size, while the piezometer placement step is usually significantly higher (literally by orders of magnitude) than this value.

In order to level out this disadvantage of the tailings monitoring system, it is reasonable to use sensor networks with greater coverage continuity. At the same time, to reduce the piezometric network step is extremely costly from the economic point of view. Under these conditions, the use of fiber-optic sensor technologies of DAS (distributed acoustic sensing, [4–8]), which are used either as a supplement to the conventional piezometer network or instead of it, looks attractive. The fiber-optic sensor DAS monitoring system is placed inside the dam body in such a way as to maximize the area of seismoacoustic emission field control of the dam body. Particular attention, in this case, is paid to critical areas the location of which is determined at the stage of structural design. Since infiltration processes, due to their own physical nature, are quite powerful seismoacoustic emission sources (SES), DAS monitoring system allows you to effectively monitor the places of occurrence and development of SES of this type inside the dam body for rapid assessment of their power and size, as well as to assess the intensity of infiltration processes in general. The DAS monitoring system can monitor almost the entire body of the dam if the fiber-optic sensor is properly installed. Fig. 2 shows a schematic representation of the DAS monitoring system installation in the body of a bulk tailings dam. Here FOS – fiber-optic sensor located inside the dam body.

In this paper, the focus is on the infiltration processes monitoring in the tailings dam embankment body, so the examples and illustrations will refer to this particular case. At the same time, the proposed methodology of control is universal and therefore can be used to control the infiltration dynamics of hydraulic structures of other types.

The contribution of this paper is given below.

— A digital twin of the infiltration processes dynamics in the body of the hydro-technical monitoring structure is proposed.
— On the basis of this model, a method of risk assessment of a hydraulic structure failure under the infiltration

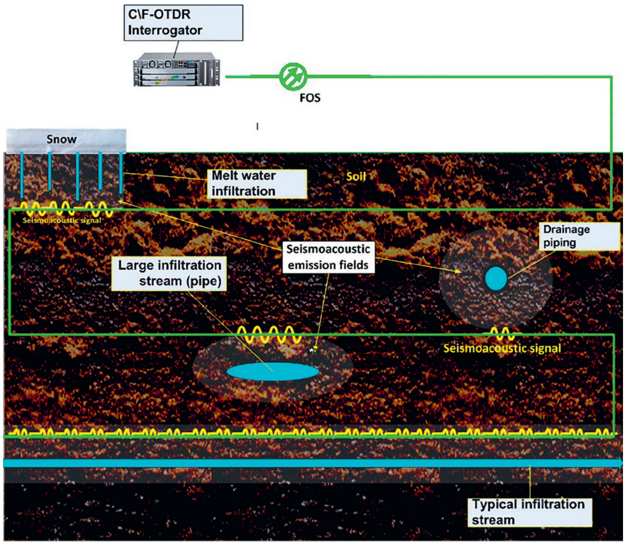

Fig. 2. Installation scheme of DAS monitoring system in the tailings dam body.
Here C\F-OTDR is Coherent/Phase-Sensitive Optical Time Domain Reflectometer

process dynamics, which was promptly observed by means of DAS systems, is proposed.

— We propose a ML-classifier (machine learning based classifier) designed for selection (detection and classification) of infiltration activities based on their seismoacoustic signatures and which functions on the basis of the original feature space. High efficiency of this ML-classifier is proved by its testing on the specialized Data Set. In particular, the performance of the ML-classifier in the situation when seismoacoustic signals from the target infiltration assets are received in the mixture with seismoacoustic signals of non-target nature is proved.

Related Work

In recent years, interest in the use of DAS systems for monitoring hydraulic structures has increased: several companies offer DAS as a component of the monitoring system of hydraulic structures, including tailings. We are talking about the companies “Silixa”, “Field Electronics”, “Terra15”, “Luna Innovations”, which in 2020 acquired the oldest player in the DAS market the company “OptaSense”, and “Institute of Mine Seismology”. At the same time, there are relatively few scientific publications on this topic. The exceptions are the papers [9–13].

The paper [9] provides general information about fiber-optic monitoring, gives a brief overview of related technologies. The disadvantages of this work include the lack of a description of the mathematical support of the system which makes it impossible to assess its capabilities. The methods of sensor installation presented in the text of this article seem to be very controversial, because they involve placing the sensor not in the body of the building, but on its surface. A very informative review [10] is devoted to the use of DAS systems for monitoring infiltration processes in hydraulic structures within the Ambient Noise Interferometry (ANI) methodology [14]. In contrast to [9], the sensor installation scheme presented in this paper is more plausible and corresponds to the principle of maximum coverage. This paper focuses not only on DAS technology, but also on other fiber-optic techniques, including fiber-optic technology for temperature measurement based on the use of Brillouin–Mandelstam radiation and Distributes Strain Sensing. The focus is on the use of ANI with DAS measurements to obtain a 3D image of the dike body. It is known that ANI makes use of naturally occurring and anthropogenic background noise to calculate seismic velocities and hence image the subsurface [14]. Here the idea is used that the background seismic noise passes through the subsurface of the structure in the same way as the signal emitted by an active (artificial) sounding source. Therefore, by studying the propagation of signals from background seismoacoustic sources, it is possible to obtain the same information that can be obtained from active sounding. DAS is used as a sensing system. In [10] the use of a digital twin of the infiltration processes dynamics in the body of the structure is not mentioned, also there is no information on how the built 3D model of the dam body will be used to assess the current state of the structure (no risk assessment methodology is given). Also there is no information about the effectiveness of mathematical support of the system in solving the problem of selection (detection and identification) of target signals from infiltration processes. It should be remembered that the target signals can be quite weak and are always received in a mixture with interfering signals. Therefore, the methods for solving the problem of selection of these signals are very important. In fact, almost the entire paper [10] is devoted to the peculiarities of cross-channel data processing of the DAS system, which is implemented to estimate local sound propagation velocities in the dam body, as well as the details of building a 3D image of the dam body. Work [11] is a brief comparative review of technical capabilities of monitoring hardware, including DAS. In [12], in addition to general technical information about OptaSense DAS interrogator, an adequate scheme of sensor installation in the dam body is proposed.

In contrast to the papers mentioned above, the method proposed in the present work to include DAS system in the monitoring loop of infiltration processes of a hydraulic structure body has a system basis. In this case, the data coming from DAS system is analyzed in order to directly assess the risk of structural failure which brings a deviation of the observed infiltration processes from the norm. The norm is defined by the parameters of the digital twin which describes the normal dynamics of infiltration processes. In addition, this paper details a new technique for highly efficient infiltration signals recognition. This technology is based on machine learning and is designed to recognize signals from infiltration processes in the body of the structure under conditions where signals are received by the DAS system in a mixture with non-target signals of a different nature and which should not be taken into account in the risk analysis.

Objectives and Method

The objectives of this work are:

— Creation of a digital twin model of infiltration processes (DTIP) developing inside the hydraulic structure body.

— Development of a methodology designed for operational assessment of the damage risk of hydraulic structures under the influence of infiltration processes developing within the structure body. The methodology is based on the simultaneous use of DTIP and operational fluid migration monitoring data in the hydraulic structure body. These data are obtained through the use of the DAS monitoring system.

— Development of ML-classifier based on the use of original feature space and modern methods of machine learning to solve the problem of infiltration activity signal detection and classification.

Let's denote:

— $X \subseteq R^3$ is a set of coordinate points of a hydraulic structure;

— $\mathbf{h}(\mathbf{x}) = (h(<\mathbf{x}>_1), h(<\mathbf{x}>_2), h(<\mathbf{x}>_3))$ is the vector of the fluid head at the point $\mathbf{x} \in X$;

— $\nabla^T\mathbf{h}(\mathbf{x}) = \left(\frac{\partial h(\mathbf{x})}{\partial x}, \frac{\partial h(\mathbf{x})}{\partial y}, \frac{\partial h(\mathbf{x})}{\partial z}\right)$ is fluid head gradient $\mathbf{h}(\mathbf{x})$;

— $K(\mathbf{x}) = (k_x(\mathbf{x}), k_y(\mathbf{x}), k_z(\mathbf{x}))$ is three-dimensional vector of permeability coefficients which characterizes the volumetric permeability of the porous medium at the point $\mathbf{x}$.

The movement of groundwater, according to the laws of fundamental continuum mechanics, obeys the Darcy's equation [14], which can be written in the following form:

$$\mathbf{v}(\mathbf{x}) = -K(\mathbf{x})\cdot\nabla^T\mathbf{h}(\mathbf{x}),$$

where $\mathbf{v}(\mathbf{x})$ is the fluid filtration rate at point $\mathbf{x}$. From the concepts of hydraulics, it is easy to obtain the basic differential equation for the steady-state fluid flow:

$$K(\mathbf{x})\cdot\mathbf{H_h}^T(\mathbf{x}) = 0, \quad (1)$$

where $\mathbf{H_h}(\mathbf{x})$ is hessian fluid head $\mathbf{h}(\mathbf{x})$. Equation (1) is solved numerically, and the result is an estimate of the piezometric head function $\mathbf{h}^E(\mathbf{x})$ and gradient estimation $\mathbf{h}^E(\mathbf{x})$ in the form of $\nabla^E\mathbf{h}(\mathbf{x})$. From Darcy's equation we get:

$$\mathrm{v}^{(E)}(\mathbf{x}) = -K(\mathbf{x})\cdot(\nabla^E\mathbf{h}(\mathbf{x}))^T. \quad (2)$$

Equation (2) describes the procedure of obtaining a numerical estimate $\mathrm{v}^{(E)}(\mathbf{x})$ for the infiltration rate at the point $\mathbf{x}$. In fact, (2) is the mathematical basis of the DTIP. Based on (2), uniformly over the entire body of the structure, a map of normal infiltration flow rates is calculated; this is used as the basis for assessing the current state of infiltration activity. In fact, DTIP is the following set:

$$\mathrm{DTIP} = \{\mathrm{v}^{(E)}(\mathbf{x})|\mathbf{x} \in X\}.$$

DTIP is determined as a result of numerical modeling of infiltration processes in the hydraulic structure body using one of the platforms for multiphysics modeling of hydrodynamic processes by finite element method, taking into account stress and strain in the ground. Such modeling can be implemented, for example, on the PLAXIS platform[1].

The principle of DAS system functioning, otherwise called C\F-OTDR system, [4–8] involves measuring the distributed strain rate of the optical fiber of the fiber optic cable which is caused by oscillatory pressure changes on the sensor surface. This oscillatory pressure is associated either with the impact of seismoacoustic waves or with the impact of a fluid that flows over the surface of the fiber optic cable [6]. The mechanism of fluid impact on the sensor surface is schematically shown in Fig. 3.

Numerous observations, some of which are described in this paper, have shown that the effect of the fluid on the fiber-optic sensor is oscillatory in nature. It is important that the period duration of the dominant harmonic of these oscillations does not exceed the value of 3–5 s. On the other hand, tests [6] showed a linear dependence between the DAS strain gradient and the fluid pressure gradient for short periods of oscillations (less than 10 s). According to the principle of its device [5–9], the DAS system is able to measure some scalar parameter which informatively characterizes the generalized deformation rate of the optical sensor (averaged over a certain time interval, T). Based on the above, the estimate $\mathrm{v}^{(R)}(\mathbf{x})$ of the real fluid infiltration rate, measured at point $\mathbf{x}$ with the DAS system, is approximated by the following linear relationship:

$$\mathrm{v}^{(R)}(\mathbf{x}) = \Phi(\mu)\cdot D(\mathbf{x}|T)\,. \quad (3)$$

[1] PLAXIS Geotechnical Analysis Software: URL: https://www.bentley.com/en/products/brands/plaxis (accessed: 19.01.2022).

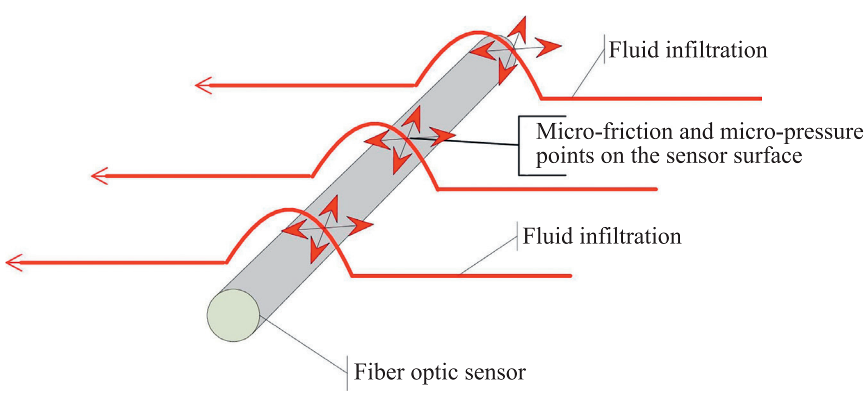

Fig. 3. Fluid impact on the surface of the fiber optic sensor

Here $\Phi(\mu)$ is a scalar calibration function that depends on the type of soil μ, which is determined as a result of in-situ experiments.

For an arbitrary point $\mathbf{x} \in X$, let us represent the value of the relative deviation of the infiltration rate from the calculated value in the following form

$$\Delta_{ER}(\mathbf{x}) = 100 \cdot (\nu^{(E)}(\mathbf{x}) - \nu^{(R)}(\mathbf{x}))/\nu^{(E)}(\mathbf{x}) .$$

Let's denote: $\mathbf{\Delta}_{ER}{}^{X}$ — matrix of relative mismatches $\nu^{(E)}(\mathbf{x})$ and $\nu^{(R)}(\mathbf{x})$ all over X,

$$\forall \mathbf{x} \in X{:}\mathbf{\Delta}_{ER}^{X}(\mathbf{x}) = \Delta_{ER}(\mathbf{x}).$$

According to the essence of the strength calculation inherent in the design of the hydraulic structure, the most stable state of the structure corresponds to the situation when $\forall \mathbf{x} \in X{:}\Delta_{ER}(\mathbf{x}) = 0$. Thus, if in all $\mathbf{x} \in X$ the value of $\Delta_{ER}(\mathbf{x}) = 0$, then the infiltration processes in the structure body are not out of control and therefore the risk of destruction of the structure, due to the impact of infiltration processes, is considered to be minimal. Conversely, the more the value $\Delta_{ER}(\mathbf{x})$ differs from zero, the higher the risk of infiltration processes getting out of control at least at point $\mathbf{x} \in X$.

At the stage of hydraulic structure calculation, a scalar loss function $L(\Delta|\mathbf{x})$ is determined, which indicates a potential damage that the structure will incur in the event of infiltration failure of this structure body at point $\mathbf{x} \in X$, at the value of the relative deviation of the infiltration processes rate from the calculated value by Δ (measured in percent). The $L(\Delta|\mathbf{x})$ function can be assigned by expert methods or determined as a result of strength calculations. In the simplest case, the loss function $L(\Delta|\mathbf{x})$ can have a point type and take values from a finite score set of small power (no more than 10). Also at the stage of calculation, the function $\rho(\Delta(\mathbf{x}))$ is determined which describes an approximate value of the probability density for the event ω_F: "the relative deviation of the infiltration process rate from the calculated value by the value $\Delta(x)$ (%)". Since in practice the density function $\rho(\Delta(\mathbf{x}))$ is unknown, for the purpose of risk assessment it is reasonable to use an approximation of this function, for example, "nuclear": $\rho^*(\Delta(\mathbf{x}))$. This approximation has the following properties: $\rho^*(x)$ is a continuous bell-shaped function, positive over the whole definition area, $\rho^*(x) = \rho^*(-x)$, $\int\limits_X (\rho^*(x))^2 dx < \infty$, $\sup\limits_x |\rho^*(x)| < \infty$, $\int\limits_{-\infty}^{\infty} \rho^*(x) = 1$. All these conditions are satisfied by the classical Gaussoid: $\rho_G{}^*(x) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{x^2}{2}\right)$.

In addition, consider the value $P(\Delta(\mathbf{x})|a_x)$ — the probability of the event ω_H: "the occurrence of a fracture zone at point $\mathbf{x}$ if the value of the relative deviation of the infiltration process rate from the calculated value equal $\Delta(\mathbf{x})$ (%)". In the general case, $P(\Delta(\mathbf{x})|a_x)$ increases monotonically with the growth of $|\Delta(\mathbf{x})|$, and the nature of the monotonicity is determined by the strength properties of the hydraulic structure body at point $\mathbf{x}$. Practically, the following approximation is appropriate: $P(\Delta(\mathbf{x})|a_x) = 1 - a_x \cdot (\Delta(\mathbf{x}) + a_x)^{-1}$ (Fig. 4). The value of the parameter a_x determines the rate of increase of $P(\Delta(\mathbf{x})|a_x)$ and depends on the hydraulic

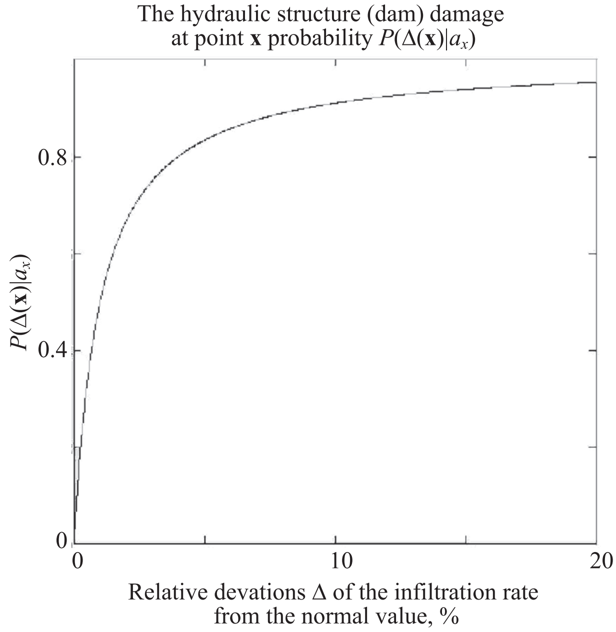

Fig. 4. Function $P(\Delta(\mathbf{x})|a_x)$

permeability and strength of the structure material in the vicinity of point $\mathbf{x}$.

Consider the assessment of the risk of hydraulic structure failure under the influence of infiltration processes, which develop in the structure body under the observed matrix $\mathbf{\Delta}_{ER}{}^{X}$, in the following form:

$$R(\mathbf{\Delta}_{ER}^{X}) = \int\limits_X P_c(\mathbf{x}) \cdot L(\Delta_{ER}(\mathbf{x})) \cdot \rho_G{}^*(\Delta_{ER}(\mathbf{x}))d\mathbf{x} + \\ + \int\limits_X P_c(\mathbf{x}) \cdot \chi(\Delta_{ER}(\mathbf{x})|p, C) \cdot P(\Delta(\mathbf{x})|a_x)d\mathbf{x} . \quad (4)$$

In (4) the following notations are used:

— $\chi(\Delta_{ER}(\mathbf{x})|p, C) = \begin{cases} \Delta_{ER}(\mathbf{x}) < p, 0 \\ \Delta_{ER}(\mathbf{x}) \ge p, C \end{cases}$;

— parameters p (threshold) and C (penalty for exceeding the threshold) are selected as a result of numerical modeling of infiltration processes in the hydraulic structure body, in the process of DTIP creation;

— $P_c(\mathbf{x})$ is the probability of detection by the monitoring system of the infiltration process that develops at point $\mathbf{x}$. In fact, we are talking about the detection of precursors of the creation of conditions for the beginning of a destructive process at point $\mathbf{x}$. The method for estimating this parameter is given in the next section of the article.

In (4), component $\int\limits_X P_c(\mathbf{x}) \cdot L(\Delta_{ER}(\mathbf{x})) \cdot \rho_G{}^*(\Delta_{ER}(\mathbf{x}))d\mathbf{x}$ corresponds to the conservative (stable) scenario of the infiltration processes dynamics in the hydraulic structure body. Within this scenario, possible deviations of infiltration rate from the calculated values are steadily rare, and the risks of destruction of the structure are manageable. On the other hand, component $\int\limits_X P_c(\mathbf{x}) \cdot \chi(\Delta_{ER}(\mathbf{x})|p, C) \cdot P(\Delta(\mathbf{x})|a_x)d\mathbf{x}$ corresponds to the radical scenario of infiltration processes development. Within this scenario, due to latent defects of the hydraulic structure body material in the point $\mathbf{x}$, infiltration processes begin to develop sharply intensively and with high probability deviate from their calculated values. As latent defects in a bulk tailings dam, for example, large ice aggregates can be considered which are often placed in the dam body during the construction phase under cryolithozone conditions. In the process of climate change, gradually, these inclusions begin to melt leading to the formation of voids and loosening of the dam body. Thus, conditions are created for sharp intensification of infiltration processes which can lead to the destruction of the dam. Since the number of DAS system channels is finite, expression (4) should be modified as follows:

$$R_K(\mathbf{\Delta}_{ER}^X) = \sum_{k\in K} P_c(\Delta_k)\cdot L(\Delta_k)\cdot \rho_G{}^*(\Delta_k) + \\ + \sum_{k\in K} P_c(\Delta_k)\chi(\Delta_k|p, C)\cdot P(\Delta_k|a_k).$$

Here k is the channel index of the DAS system; K is the set of indexes of the channels of this system; and Δ_k is the value of the parameter $\Delta_{ER}(\mathbf{x}_k)$ from (3) at the point $\mathbf{x}_k$ of the location of the k-th channel of the system.

Since the risk function is designed to estimate the deviation degree of the current state of a hydraulic structure from the normal one, which corresponds to the value $R_K(0)$, the decision about exceeding the current risk of the permissible value is made in the following case:

$$\ln\left(\frac{R_K(\mathbf{\Delta}_{ER}{}^X)}{R_K(0)}\right) \geq \lambda.$$

Here λ is the scalar threshold selected according to the results of numerical simulation within DTIP, individually for each hydraulic structure.

Infiltration signal classification and $P_c(\mathbf{x})$ estimation

The most important part of the hydraulic structure monitoring data processing system is a subsystem for automatic classification of the SES type whose signal was received by DAS system. This is important because when forming the estimate $\nu^{(R)}(\mathbf{x})$ in (3), the monitoring system must take into account signals from infiltration-type SES only that are always received by DAS system in superposition with signals of noise signals (signals from non-target SES's). In the case of using a DAS system, each of its channels receives data about the state of the seismoacoustic field of the hydrostructure body at the location of this channel. Let's consider the case when the task of detecting target SES sources is solved in each channel independently, and cross-channel, integral data processing is performed already at the following stages of processing. In this case, a stream of raw data coming from the k-th channel of the system is processed on the basis of a sequence of time intervals $T_i(\delta) = (t_i^S, t_i^E)$, $t_i^E = t_i^S + \delta$, $i \geq 0$ of equal length δ, sometimes called "windows". A time window $T_i(\delta)$ is characterized by a pair (t_i^S, t_i^E), where t_i^S is the moment of the beginning of the time interval, and t_i^E is the moment of its termination.

To reduce the unwieldiness of the record, let us assume that $T_i(\delta)$ consists of δ samples. Each time interval $T_i(\delta)$ in the k-th channel corresponds to a set of channel measurements $\lambda(T_i(\delta))$ (raw data), $\lambda(T_i(\delta)) \in \Lambda$ which were obtained during this interval in this channel and which characterize the dynamics of the seismoacoustic field at point $\mathbf{x}_k$. Here Λ is the set of all possible realizations of $\lambda(T_i(\delta))$. Let the set $\Pi = \{\pi_i | i = 1, \ldots, N\}$ contain all target SES types, including the background class. The task is to construct a classifier D such that

$$\Lambda \xrightarrow{\mathrm{D}} \Pi,\ \forall i \geq 0{:}\pi = \mathrm{D}(\lambda(T_i(\delta))) \in \Pi. \quad (5)$$

As indicated earlier, the background class (class of generalized noises and non-target SES belongs to the set Π. Therefore, the classification problem (5) implicitly includes the problem of detecting the target SES. When building a classifier D using machine learning methods, the choice of feature space **F** plays a special role. When forming **F**, initially, we considered a set consisting of more than 40 features. At subsequent stages, this set was reasonably narrowed down by selecting the most informative features. Several methods were used including three so-called "filtering" methods: chi-square, Pearson correlation and analysis of variance (ANOVA), as well as adaptive method of backward elimination. As a result, the following set f_λ of features was obtained:

$$f_\lambda = (\mathbf{E}[\lambda], |\lambda|, ST(\lambda), H_m(\lambda), r_\lambda, E^*(A_\lambda(l)), |A_\lambda(l)|, st^*(A_\lambda(l))).$$

Here

— $\lambda \in \Lambda \subseteq R^\delta$; $<\lambda>_p$ is p-th component of λ;

— $E[\lambda] = \sum_p <\lambda>_p \delta^{-1}$;

— $|\lambda| = \max_p(<\lambda>_p) - \min_p(<\lambda>_p)$:

— $ST(\lambda) = (\sum_p(\mathbf{E}[\lambda] - <\lambda>_p)^2\cdot\delta^{-1})^{0.5}$;

— $H_m(\lambda)$ is histogram of λ with m bins;

— $A_\lambda(l)$ is autocorrelation function of the λ, $l \in (0, \delta)$ is shift;

— r_λ is radius correlation of λ;

— $E^*(A_\lambda(l)) = \sum_{l\geq r_\lambda} A_\lambda(l)(\delta - r_\lambda)^{-1}$;

— $|A_\lambda(l)| = \max_{l\geq r_\lambda}(A_\lambda(l)) - \min_{l\geq r_\lambda}(A_\lambda(l))$;

— $st^*(A_\lambda(l)) = (\sum_{l\geq r_\lambda}(E^*(A_\lambda(l)) - A_\lambda(l))^2(\delta - r_\lambda - 1)^{-1})^{0.5}$.

In numerical studies it was assumed that $m = 20$. The features f_λ are defined in the corresponding feature space **F**, consisting of real vectors of length 27.

To train and test the classification algorithm, we used a Data Set collected at several different test sites, at different times of the year. This Data Set included three-second samples of fluid dynamics signals of the following types:

— Class 0: small underground river, name: "River Flow Sound", 509 samples, Fig. 5;

— Class 1: noise of melting snow infiltration, name: "Melting Snow Flow Sound", 1059 samples, Fig. 6;

— Class 2: noise from an underground drainage pipeline, name: "Pipe Flow Sound", 339 samples, Fig. 7;

— Class 3: background seismoacoustic noise, name: "Background sound", 1168 samples, Fig. 8.

Fig. 6–9 show a typical histogram, autocorrelation function, and waterfall diagram for classes 0–3.

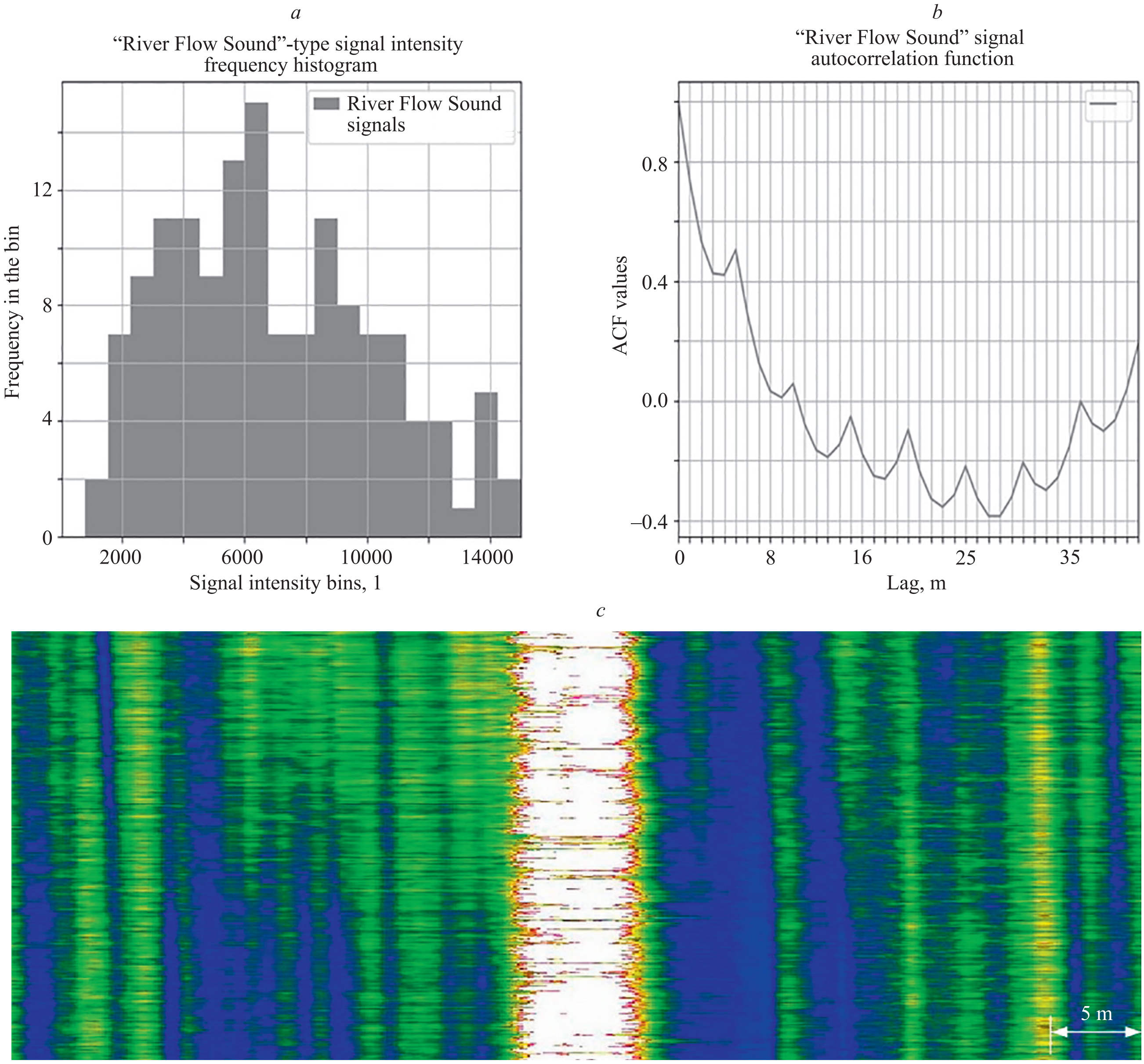

Fig. 5. Typical histogram (*a*), autocorrelation function (*b*), and waterfall diagram (*c*) for class 0, “River Flow Sound”

As can be seen from the behavior of the autocorrelation functions of signals of different classes, they all have an oscillatory nature. Moreover, the period of the dominant harmonic of these oscillations does not exceed the value of 3–5 s.

Since the dimensionality of feature space **F** is relatively small, and the signals in Data Set have a relatively large r_λ value, the samples of the same class will relatively “smoothly” differ from each other by the metric of feature space. Under these conditions, it is logical to use as a D-classifier a conventional and very computationally economical multi-class SVM (MC-SVM) [15]. During training, in order to ensure control of the generalization ability of the classifiers, the standard Cross Validation scheme was used, in the LOO (leave-one-out) variant. For the MC SVM classifier, given the multiclass formulation of the problem, a one-vs-rest strategy was used.

The results of the numerical studies are summarized in Tables 1 and 2. The main information is contained in Table 1. Here we accumulate the results which were shown on the test Data Set by classifiers based on MC SVM. A standard set of metrics was used to evaluate the classification results: precision, recall, and f1-score. The “support” column contains the number of samples of each class that were used in the test. Table 2 shows the so-called confusion matrix obtained as a result of the numerical experiment. The quality metrics of Table 1 indicates a very high quality of infiltration event classification. On the other hand, the confusion matrix (Table 2) shows that only the River Flow class causes small problems in classification: several samples from other classes were mistakenly assigned to this class. This is due to the fact that this infiltration class is quite close in its physical nature to other infiltration classes. Importantly, the vast majority of classification errors were due to confusion within the infiltration classes. All these classes are target classes for the monitoring system; the main thing is that the system classifier should be able to qualitatively distinguish

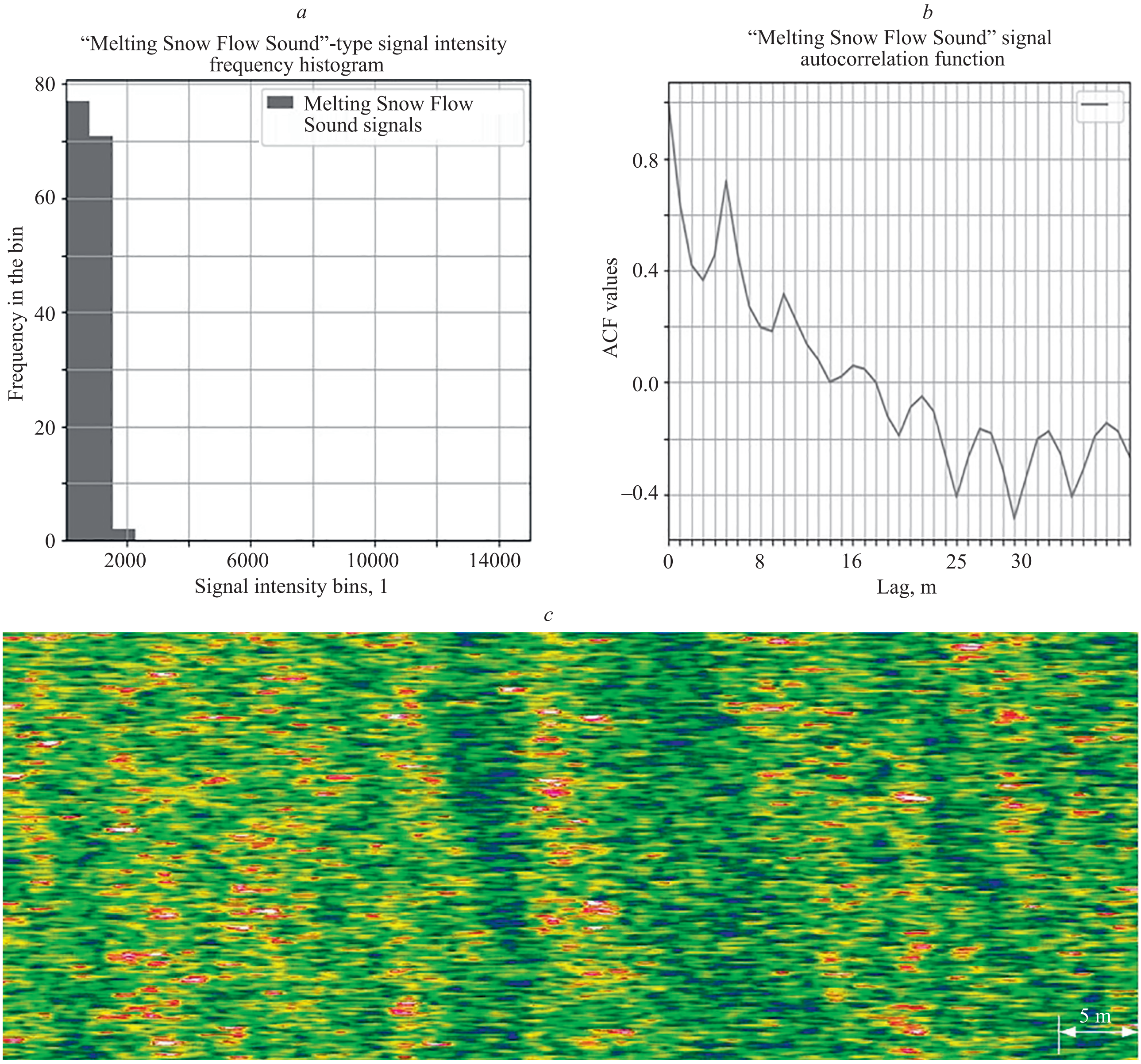

Fig. 6. Typical histogram (*a*), autocorrelation function (*b*), and waterfall diagram (*c*) for class 1, “Melting Snow Flow Sound”

Table 1. The basic metrics values on the test Data Set

SES class name	Precision	Recall	f1-score	Support
River Flow	0.96	1.00	0.98	128
Melting Snow Flow	1.00	0.99	0.99	276
Pipe Flow	1.00	0.99	0.99	75
Background	1.00	1.00	1.00	290

Table 2. Confusion matrix

SES class	River Flow	Melting Snow Flow	Pipe Flow	Background
River Flow	128	0	0	0
Melting Snow Flow	4	272	0	0
Pipe Flow	1	0	74	0
Background	1	0	0	289

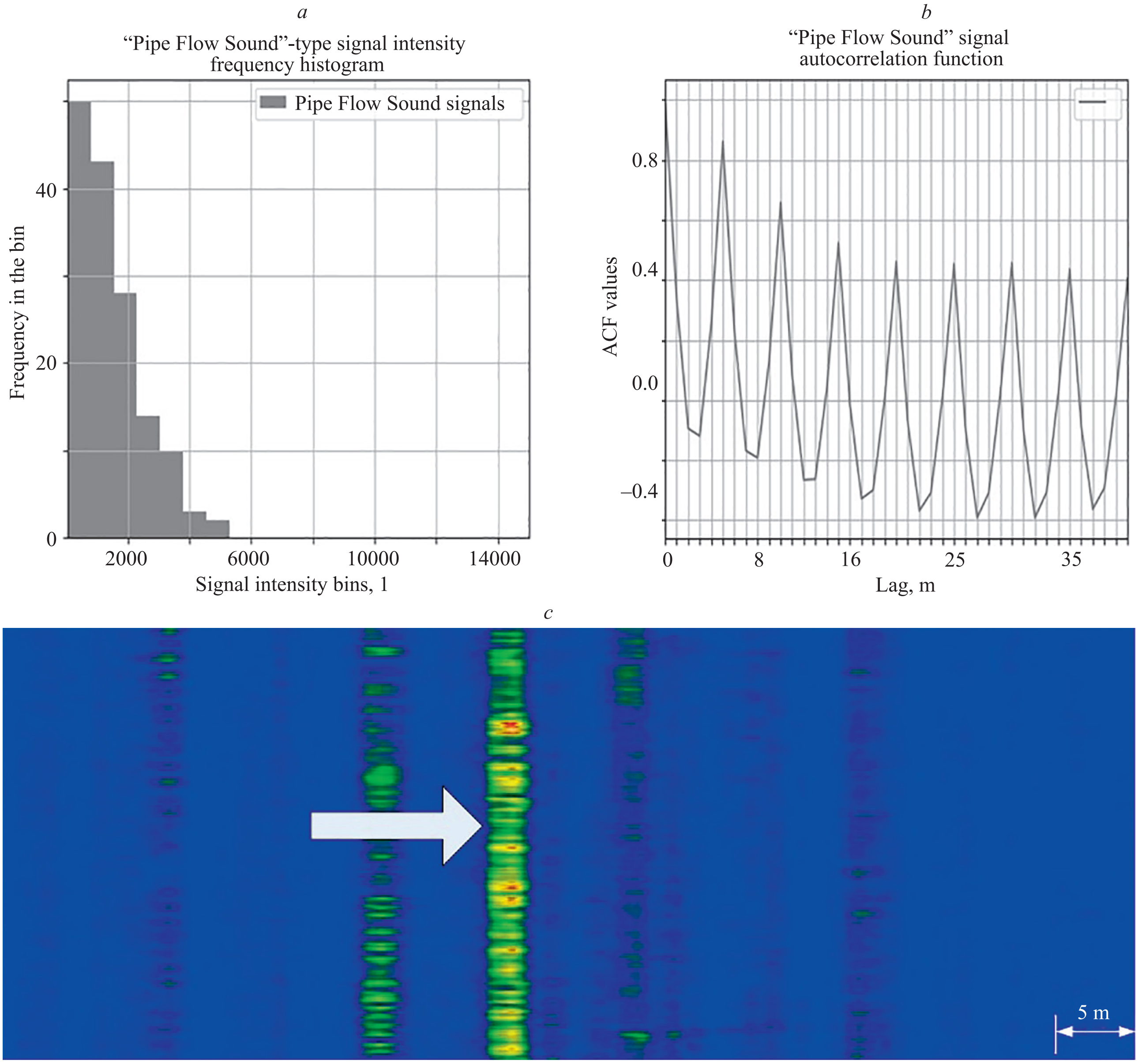

Fig. 7. Typical histogram (*a*), autocorrelation function (*b*), and waterfall diagram (*c*) for class 2, “Pipe Flow Sound”

the signals of this type, distinguishing them from the background or noise signals. Only one error represents confusion with a non-target (non-infiltration) class (background). This is a very qualitative result. In general, the classification results are close to perfect. Thus, it is shown: the DAS system detects and classifies infiltration SES very well. It is logical to use the class-averaged f1-score as an estimate of the $P_c(\mathbf{x})$ value from (4).

Engineering aspects of DAS system installation on a hydraulic facility

The main problem that arises when installing a fiber-optic monitoring system for a hydraulic structure is the installation of the fiber-optic sensor in the body of the hydraulic structure. The principle of installation is simple: as much coverage as possible of the structure’s body volume in critical areas. Critical areas are determined at the stage of design of a structure and, as a rule, are located in the areas below the calculated plane of depression (which in the 2D case is called the depression curve). The depression plane is the geometric location of the points of the upper boundary line of the infiltration processes flow in the case of conservative (normal) scenario. Fig. 9 shows a possible way of installing a fiber-optic sensor in the body of the tailings dam. The sensor stacking step depends on the sensitivity of the DAS system and for target SES’s is approximately 5 m. In order to maximize the seismoacoustic field control of the hydraulic structure dam, the sensor is placed inside the dam body volume according to the principle of maximum coverage.

Discussion

The monitoring method considered in this article, on the one hand, allows with high reliability and continuity

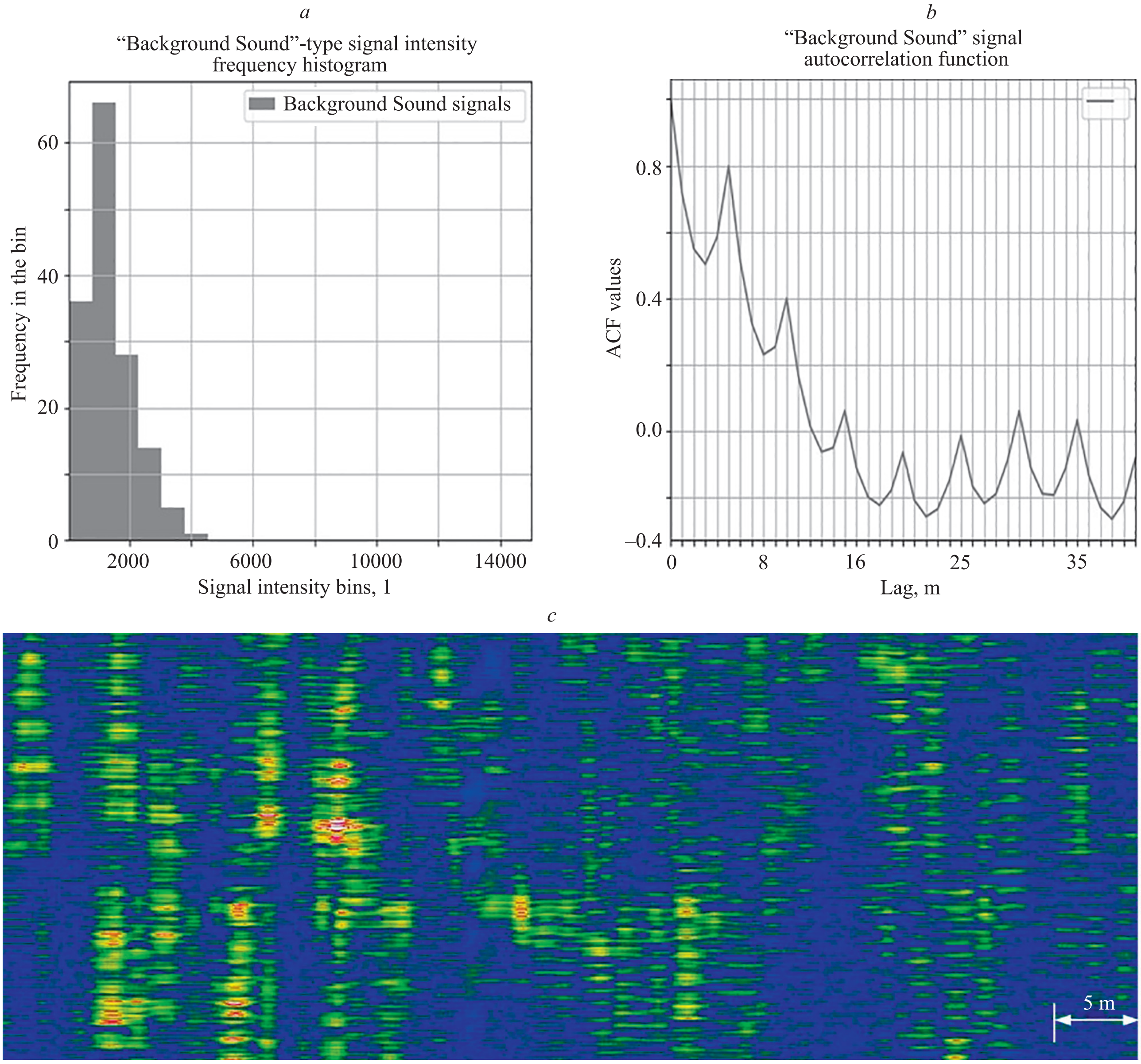

Fig. 8. Typical histogram (*a*), autocorrelation function (*b*), and waterfall diagram (*c*) for class 3, "Background sound"

to control sufficiently long (perimeter 5–20 km and more) facilities, and on the other hand — indicates the way to monitor effective use of data for formal risk analysis of the operation of a particular object. The use of a digital twin of the infiltration activity inside the object body allows us to determine threshold values in risk management procedures, and the application of AI/ML methods for signal source type classification, with high reliability (this property is proved by materials of this work) to distinguish only target signals, caused by infiltration activities. Of course, the ideal solution to the monitoring task would be the use of a highly sensitive high-density piezometric network which would evenly (solidly) cover the entire body of the object. But such a solution is practically unavailable, due to the enormous cost of both the piezometer-type sensor network installation in the body of the structure and the high cost of owning this network. The fact is that point sensors will require constant service, including repairs, replacement of batteries, monitoring of communication channels, and periodic status checks of hundreds of point sensors to ensure

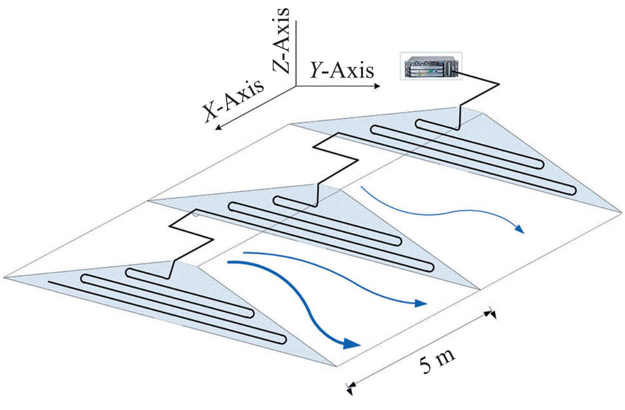

Fig. 9. Installation of a fiber-optic sensor in a tailings dam body

that literally every sensor is compliant with the instrument certificate. In these conditions, DAS monitoring system, slightly inferior in sensitivity and accuracy piezometric network, looks extremely promising and a compromise solution if we compare alternative systems in the criteria space of "price-quality-functionality". The sensor of a DAS system does not require maintenance and remains operational for decades, only the system interrogator needs service. But this device is manufactured in accordance with the highest standards of communication equipment and it is able to function for 5–6 years or more in harsh climatic conditions, almost without maintenance. An additional bonus of using the DAS monitoring system is its extreme unpretentiousness: authors of the article have experience of non-stop, trouble-free operation of the interrogator for 6 years, and the temperature in the room where the interrogator was located reached +40 °C in summer and dropped to –25 °C in winter. These qualities are especially valuable when monitoring objects located in the cryolithozone, for example, for tailings dams with bulk dams.

Conclusion

Having achieved all the goals that have been set in this paper, the authors plan to focus in the future on solving the following tasks aimed at the practical strengthening of the proposed solution:
- DTIP model refinement;
- Refining the methodology designed to estimate the risk of damage to a hydraulic facility due to uncontrolled development of infiltration processes;
- Development of DTIP-based methods of forecasting the development of the infiltration processes dynamics inside specific hydraulic structure body;
- Development of technology for optimal installation of a fiber-optic sensor in the specific hydraulic structure body.

References

1. Sukhno A.M., Khlapov N.N. Automatic system for monitoring at the tailing storage of Aikhal'sky mining and concentrating works. *Gornyi Zhurnal*, 2008, no. 5, pp. 65–68. (in Russian).
2. Besimbaeva O.G., Khmyrova E.N., Loginov A.V., Oleinikova E.A. Research of the opportunities of 3D modeling for mine surveying support of mining works. *Interexpo GEO-Siberia*, 2017, vol. 1, no. 1, pp. 125–129. (in Russian).
3. Aravin V., Numerov S. *The Theory of Motion of Liquids and Gases in Non-Deformable Porous Medium*. Moscow: Gosudarstvennoe izdatel'stvo tehniko-teoreticheskoj literatury, 1953, 616 c. (in Russian).
4. Timofeev A.V., Groznov D.I. Classification of seismoacoustic emission sources in fiber optic systems for monitoring extended objects. *Optoelectronics, Instrumentation and Data Processing*, 2020, vol. 56, no. 1, pp. 50–60. https://doi.org/10.3103/S8756699020010070
5. Timofeev A.V., Denisov V.M. Multimodal heterogeneous monitoring of super-extended objects: Modern view. *Studies in Systems, Decision and Control*, 2016, vol. 62, pp. 97–116. https://doi.org/10.1007/978-3-319-32525-5_6
6. Becker M., Coleman T., Ciervo C., Cole M., Mondanos M. Fluid pressure sensing with fiber-optic distributed acoustic sensing. *Leading Edge*, 2017, vol. 36, no. 12, pp. 1018–1023. https://doi.org/10.1190/tle36121018.1
7. Liu X., Jin B., Bai Q., Wang Y., Wang D., Wang Y. Distributed fiber-optic sensors for vibration detection. *Sensors*, 2016, vol. 16, no. 8, pp. 1164. https://doi.org/10.3390/s16081164
8. Wang Y., Jin B., Wang Y., Wang D., Liu X., Bai Q. Real-time distributed vibration monitoring system using Φ –OTDR. *IEEE Sensors Journal*, 2017, vol. 17, no. 5, pp. 1333–1341. https://doi.org/10.1109/jsen.2016.2642221
9. Inaudi D., Cottone I., Figini A. Monitoring dams and levees with distributed fiber optic sensing. *Proc. of the 6th International Conference on Structural Health Monitoring of Intelligent Infrastructure*, 2013.
10. Johansson S., Beaupretre S., Boue A., Stork A. *Distributed Acoustic Sensing for Detection of Defects in the Test Dam at Älvkarleby*. Technical Report. 2021. Available at: https://energiforsk.se/en/programmes/dam-safety/reports/distributed-acoustic-sensing-for-detection-of-defects-2021-732/ (accessed: 15.12.2021).
11. Ouellet S., Suszek N., Lato M., Russell B., Froese C., Carey E. Static liquefaction-type tailings dam failures: understanding options for detecting failures. *Proc. of Tailings and Mine Waste, November 17–20 2019. Vancouver, Canada*. University of British Columbia, 2019, pp. 415–420.
12. Forbes B., Ouellet S., Suszek N., Lato M., Russell B. Application of distributed acoustic sensing within a tailings dam warning system. *Proc. of Tailings and Mine Waste Conference*, 2021.

Литература

1. Сухно А.М., Хлапов Н.Н. Автоматизированная система мониторинга на хвостохранилище Айхальского ГОКЕ // Горный журнал. 2008. № 5. С. 65–68.
2. Бесимбаева О.Г., Хмырова Е.Н., Логинов А.В., Олейникова Е.А. Мониторинг состояния дамбы хвостохранилища намывного типа // Интерэкспо ГЕО-Сибирь. 2017. Т. 1. № 1. С. 125–129.
3. Аравин В.И., Нумеров С.Н. Теория движения жидкостей и газов в недеформируемой пористой среде. М.: Государственное издательство технико-теоретической литературы, 1953. 616 с.
4. Timofeev A.V., Groznov D.I. Classification of seismoacoustic emission sources in fiber optic systems for monitoring extended objects // Optoelectronics, Instrumentation and Data Processing. 2020. V. 56. N 1. P. 50–60. https://doi.org/10.3103/S8756699020010070
5. Timofeev A.V., Denisov V.M. Multimodal heterogeneous monitoring of super-extended objects: Modern view // Studies in Systems, Decision and Control. 2016. V. 62. P. 97–116. https://doi.org/10.1007/978-3-319-32525-5_6
6. Becker M., Coleman T., Ciervo C., Cole M., Mondanos M. Fluid pressure sensing with fiber-optic distributed acoustic sensing // Leading Edge. 2017. V. 36. N 12. P. 1018–1023. https://doi.org/10.1190/tle36121018.1
7. Liu X., Jin B., Bai Q., Wang Y., Wang D., Wang Y. Distributed fiber-optic sensors for vibration detection // Sensors. 2016. V. 16. N 8. P. 1164. https://doi.org/10.3390/s16081164
8. Wang Y., Jin B., Wang Y., Wang D., Liu X., Bai Q. Real-time distributed vibration monitoring system using Φ -OTDR // IEEE Sensors Journal. 2017. V. 17. N 5. P. 1333–1341. https://doi.org/10.1109/jsen.2016.2642221
9. Inaudi D., Cottone I., Figini A. Monitoring dams and levees with distributed fiber optic sensing // Proc. of the 6th International Conference on Structural Health Monitoring of Intelligent Infrastructure. 2013.
10. Johansson S., Beaupretre S., Boue A., Stork A. Distributed Acoustic Sensing for Detection of Defects in the Test Dam at Älvkarleby: Technical Report. 2021 [Электронный ресурс]. URL: https://energiforsk.se/en/programmes/dam-safety/reports/distributed-acoustic-sensing-for-detection-of-defects-2021-732/ (дата обращения: 15.12.2021).
11. Ouellet S., Suszek N., Lato M., Russell B., Froese C., Carey E. Static liquefaction-type tailings dam failures: understanding options for detecting failures // Proc. of Tailings and Mine Waste, November 17–20 2019. Vancouver, Canada. University of British Columbia, 2019. P. 415–420.
12. Forbes B., Ouellet S., Suszek N., Lato M., Russell B. Application of distributed acoustic sensing within a tailings dam warning system // Proc. of Tailings and Mine Waste Conference, 2021.

13. Rasskazov L.N., Orekhov V.G., Aniskin N.A. *Hydrotechnical Constructions. Part 1*. Textbook. Moscow: Association of Civil Engineering Universities Publ., 2008. 575 p. (in Russian).
14. Shapiro N., Campillo M., Stehly L., Ritzwoller M. High-resolution surface-wave tomography from ambient seismic noise. *Science*, 2005, vol. 307, no. 5715, pp. 1615–1618. https://doi.org/10.1126/science.110833
15. Cristianini N., Shawe-Taylor J. *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*. Cambridge University Press, 2000, 189 p.

13. Рассказов Л.Н., Орехов В.Г., Анискин Н.А. Гидротехнические сооружения. Ч. 1: учебник. М.: Ассоциация строительных вузов, 2008. 575 с.
14. Shapiro N., Campillo M., Stehly L., Ritzwoller M. High-resolution surface-wave tomography from ambient seismic noise // Science. 2005. V. 307. N 5715. P. 1615–1618. https://doi.org/10.1126/science.110833
15. Cristianini N., Shawe-Taylor J. An Introduction to Support Vector Machines and Other Kernel-based Learning Methods. Cambridge University Press, 2000. 189 p.

Authors

Andrey V. Timofeev — D. Sc. (Eng.), CSO, LLP “EqualiZoom”, Astana, 010000, Kazakhstan, SC 56689367600, https://orcid.org/0000-0001-7212-5230, timofeev.andrey@gmail.com

Denis I. Groznov — Software Developer, LLP “EqualiZoom”, Astana, 010000, Kazakhstan, SC 56689367600, https://orcid.org/0000-0002-7874-7118, d.i.groznov@yandex.ru

Авторы

Тимофеев Андрей Владимирович — доктор технических наук, научный директор, ТОО «Эквалайзум», Астана, 010000, Казахстан, SC 56689367600, https://orcid.org/0000-0001-7212-5230, timofeev.andrey@gmail.com

Грознов Денис Игоревич — разработчик, ТОО «Эквалайзум», Астана, 010000, Казахстан, SC 56689367600, https://orcid.org/0000-0002-7874-7118, d.i.groznov@yandex.ru

Received 19.01.2022
Approved after reviewing 01.05.2022
Accepted 25.05.2022

Статья поступила в редакцию 19.01.2022
Одобрена после рецензирования 01.05.2022
Принята к печати 25.05.2022