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INTELLIGENT SYSTEM OF NOISE CONTROL OF THE TECHNICAL CONDITION OF RAILROAD TRACKS

Summary. It is shown that modern geometry cars, flaw detector cars and other track test cars provide reliable control of the technical condition of all hauls of the railroad track at "certain intervals of time". Their number is limited and therefore "continuous monitoring" of all hauls is almost impossible. At the same time, in real life, due to the impact of various factors, such as seismic processes, certain changes take place even a day after control. The authors consider one option for continuous monitoring of the beginning of changes in the technical condition of the track using intelligent tools, which allow one, by analyzing the useful signal and the noise from the soil vibrations caused by the rolling stock, to create informative attributes for identifying the technical condition of the track. The application of traditional technologies of correlation and spectral analysis and other methods for this purpose does not allow ensuring adequacy of the control results. This paper proposes a technology for extracting and analyzing useful vibration signals, the noise of vibration signals and the relationship between them. The estimates of both correlation and spectral characteristics of the useful signal and the noise are used as the main carriers of diagnostic information. Due to the simplicity and the reliability of implementation of the proposed technical tools, they can be easily installed in one of the cars of all rolling stocks, providing control of the beginning of changes in the technical condition of the track during their movement in all hauls.

1. INTRODUCTION

It is known that one of the main requirements for a railroad track is that all its elements, track superstructures, artificial structures and the roadbed should have adequate strength, stability and condition to ensure safe and smooth movement of trains at the speeds established for the controlled section of the track [1-6].

The control of the condition of the railroad track superstructure is mainly carried out under dynamic load [2-4]. Modern geometry cars are complex computerized systems that allow assessment of the state of the track by a variety of parameters. They have a standard trolley on one end and a special one on the other. It contains special equipment that makes all the necessary measurements, for instance, track width, twists, depressions and many other parameters. All these data are recorded on special media by recording devices. Further, after passing a section, all the necessary information about the revealed flaws enters the track maintenance department, with the aim of eliminating them as soon as possible [2]. Geometry cars are used both at reduced and at maximum speeds established for a given haul. Railroad workers also use flaw detector cars. A flaw detector car is an ordinary car with the necessary equipment and a special trolley for conducting flaw detection of rails and track switches. In recent years, self-propelled flaw detectors [3-5] equipped with radio communications have been actively introduced to transmit information about detected violations to the duty officers at stations on both ends of a haul [2-5]. In the end, all the information is sent to the track maintenance department [2-5]. However, despite these efforts, of freight and passenger train wrecks still occur frequently. This is due to the fact that it is currently impossible to carry out continuous control of the technical condition of the railway. As our studies have shown, by solving such problems as ensuring continuous control of the latent period of changes in the technical condition of railroad tracks, railroad bridges, tunnels, crossings, etc., it is possible to enhance the safety of rail transport [3, 4]. This is particularly important for rail transport in countries located in seismically active regions. This is due to the fact that weak, 1-3 point, earthquakes often occur in these regions, affecting the technical condition of the railroad tracks, bridges, tunnels and communications. They, as a rule, do not result in great destruction. However, each such earthquake is a potential factor contributing to the beginning of the latent period of changes of a facility's technical condition. In this respect, the application of technology and noise control systems in rail transport safety systems is of undoubted practical interest [2-4]. However, as the railroad passes through seismically active regions, additional requirements for traffic safety appear. Our analysis of the literature [1, 2] devoted to control technologies and control systems taking into account the specific characteristics of railroads has shown that the use of noise technologies can, due to their specifics, improve the safety of this mode of transport. To do this, it is reasonable to create a subsystem for noise control of the latent period of the beginning of malfunctions in the railbed, bridges, tunnels and communications throughout the entire railroad track.

These subsystems will allow the traffic control service to receive additional information in advance, which allows one to take appropriate actions to improve traffic safety in general.

Therefore, the development of fundamentally new intelligent technologies to obtain real-time information on the condition of the railroad track in an amount sufficient to monitor the beginning of the latent period of changes in its technical condition can be considered a relevant issue.

2. PROBLEM STATEMENT

With the development of high-speed train traffic, the requirements for objects and devices of railroad infrastructure are becoming more stringent: the condition of the rail line, the track superstructure (ballast), on which the qualitative characteristics of performance, safety and uninterrupted operation of trains depend. To ensure the safety of the track, it is necessary to obtain sufficient information to monitor the technical condition of the track ballast, the subgrade, under the ballast and sloping areas of the roadbed during the movement of the rolling stock. Due to the importance of this problem, railroads use special track test cars, geometry cars, flaw detector cars and carriages for checking and testing the overhead line. Most measuring mechanisms with sensors are located below the car body for the convenience of monitoring and maintenance. For instance, geometry cars use typical linear displacement sensors, which provide such information as linear vibrational displacements along the coordinate axes, bouncing, lateral, twitching, angular vibrational displacements relative to the coordinate axes, pitching and side rolling [2-5]. Control of the technical condition of the railroad track is practically performed by geometry cars of each haul on schedule, i.e., "in turns", as it is believed that no significant changes occur between the checks, when no control is carried out. At the same time, in real life, due to the impact of various factors, such as seismic processes, certain changes take place even a day after control. Therefore, the issue of creating new alternative solutions to improve the control of the technical condition of tracks is relevant. Obviously, in addition to the existing ones, it is advisable to create simple and inexpensive intelligent tools, which can be installed in some cars as a device controlling the beginning of changes in the technical condition of the rolling stock along the route. In this case, the information center can receive signals in real time from the trains in the hauls that need to be controlled “out of turn” [1-5]. In this respect, it is of great practical importance to create intelligent technologies for monitoring the beginning of changes in the technical condition of railroad tracks in real time during rolling stock movement.

It is advisable to take into account that one of the most effective methods of diagnostics of the technical condition of railroad tracks is based on the use of vibrations of the soil of embankments caused by the rolling stock [2-8]. The prerequisite for the application of the vibration method is that a certain condition of embankments corresponds to a group of diagnostic signs of a dynamic process that occur during the movement of trains.

Suppose that during the movement of rolling stock at the output of the vibration sensor D_V installed on the car body, the noisy sampled vibration signal $g(i\Delta t)$ is obtained. The result of the dynamic process reflecting the beginning of changes in the technical condition of the railroad track during the movement of the rolling stock affects the vibration signal $g(i\Delta t)$, which consists of the useful vibration signal $X(i\Delta t)$ and the sum noise $\varepsilon(i\Delta t)$ of the vibration signal, i.e.:

$$g(i\Delta t) = X(i\Delta t) + \varepsilon(i\Delta t) \tag{1}$$

It can be assumed that due to the impact of the technical condition of the track, due to the enormous weight of the car and rolling stock, low-frequency vibrations occur. At the same time, it can also be assumed that high-frequency components are mainly caused by other factors related to the technical condition of the rolling stock. Therefore, it can be assumed that in the sum noisy vibration signal $g(i\Delta t)$, the high-frequency components of the noise $\varepsilon(i\Delta t)$ are mostly indicative of the technical condition of the car of the rolling stock, and the useful signal consisting of low-frequency components of $\mathrm{X}(i\Delta t)$ and the relationship coefficient between $X(i\Delta t)$ and $\varepsilon(i\Delta t)$ rather reflect the information about the technical condition of the track. Therefore, by analyzing the useful vibration signal $X(i\Delta t)$, the noise $\varepsilon(i\Delta t)$ of the vibration signal and the relationship between them, it is possible to monitor the onset of changes in the technical condition of the track in any haul during the movement of the rolling stock.

This paper aims to create new technologies and tools for monitoring the technical condition of the railroad track, which, by analyzing vibration noisy signals, allow one to reveal its pre-failure states in real time without limitations of the speed of trains.

In view of the above, to monitor the beginning of changes in the technical condition of railroad track hauls during the movement of the rolling stock in real time, it is necessary to create technologies for creating and analyzing equivalent useful vibration signals $X^e(i\Delta t)$ and equivalent noise $\varepsilon^e(i\Delta t)$, allowing to obtain results similar to the results of real useful vibration signals $X(i\Delta t)$ and noise $\varepsilon(i\Delta t)$, i.e., it is necessary to ensure that the following equalities hold:

$$D_X = \frac{1}{N}\sum_{i=1}^{N} X^2(i\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} X^{e^2}(i\Delta t) = D_X^e,$$

$$D_\varepsilon = \frac{1}{N}\sum_{i=1}^{N} \varepsilon^2(i\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} \varepsilon^{e^2}(i\Delta t) = D_\varepsilon^e,$$

$$R_{XX}(\mu) = \frac{1}{N}\sum_{i=1}^{N} X(i\Delta t)X((i+\mu)\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} X^e(i\Delta t)X^e((i+\mu)\Delta t) \approx R^e_{X^eX^e}(\mu),$$

$$R_{\varepsilon\varepsilon}(\mu) = \frac{1}{N}\sum_{i=1}^{N} \varepsilon(i\Delta t)\varepsilon((i+\mu)\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} \varepsilon^e(i\Delta t)\varepsilon^e((i+\mu)\Delta t) \approx R^e_{\varepsilon^e\varepsilon^e}(\mu),$$

$$R_{X\varepsilon}(\mu) = \frac{1}{N}\sum_{i=1}^{N} X(i\Delta t)\varepsilon((i+\mu)\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} X^e(i\Delta t)\varepsilon^e((i+\mu)\Delta t) \approx R^e_{X^e\varepsilon^e}(\mu),$$

$$a_{nX} = \frac{1}{N}\sum_{i=1}^{N} \cos n\omega_j\, X(i\Delta t) \approx a^e_{nX}\, \frac{1}{N}\sum_{i=1}^{N} \cos n\omega_j\, X^e(i\Delta t) = a^e_{nX},$$

$$b_{nX} = \frac{1}{N}\sum_{i=1}^{N} \sin n\omega_j\, X(i\Delta t) \approx b^e_{nX}\, \frac{1}{N}\sum_{i=1}^{N} \sin n\omega_j\, X^e(i\Delta t) = b^e_{nX}, \tag{2}$$

$$a_{n\varepsilon} = \frac{1}{N}\sum_{i=1}^{N} \cos n\,\omega_j\, \varepsilon(i\Delta t) \approx a_{n\varepsilon}^{*e}\ \frac{1}{N}\sum_{i=1}^{N} \cos n\,\omega_j\, \varepsilon^e(i\Delta t) = a_{n\varepsilon}^{*e},$$

$$b_{n\varepsilon} = \frac{1}{N}\sum_{i=1}^{N} \sin n\,\omega_j\, \varepsilon(i\Delta t) \approx b_{n\varepsilon}^{*e}\ \frac{1}{N}\sum_{i=1}^{N} \sin n\,\omega_j\, \varepsilon^e(i\Delta t) = b_{n\varepsilon}^{*e},$$

where $X(i\Delta t)$ and $X^e(i\Delta t)$ are the useful vibration signal and the equivalent useful vibration signal, respectively; $\varepsilon(i\Delta t)$ and $\varepsilon^e(i\Delta t)$ are the noise of the vibration signal and the equivalent noise, respectively; $R_{XX}(\mu)$, $R_{\varepsilon\varepsilon}(\mu)$, $R_{X^eX^e}(\mu)$ and $R_{\varepsilon^e\varepsilon^e}(\mu)$ are the estimates of the correlation functions of the useful signal and the noise, and the estimates of the equivalent correlation functions, the useful signals and the equivalent noises, respectively; and a_{nX}, b_{nX}, , $a_{n\varepsilon}$, $b_{n\varepsilon}$, a_{nX}^e and b_{nX}^e are the spectral characteristics of the useful signals and the noises and the estimates of the spectral characteristics of the equivalent useful signals and the equivalent noises, respectively.

3. ALGORITHMS FOR ANALYSIS OF NOISY VIBRATION SIGNALS USING EQUIVALENT SAMPLES OF THEIR NOISES AND USEFUL SIGNALS

The studies showed that it is possible to control the technical condition of railroad tracks by analyzing noise vibration signals, using the technology for determining the equivalent samples of their noise $\varepsilon^e(i\Delta t)$ [1]. For this purpose, we first consider the possibility of calculating approximate quantities of the samples of the noise $\varepsilon(i\Delta t)$ of the noisy vibration signals $g(i\Delta t)$, which cannot be measured directly. An analysis of possible solutions to this problem demonstrated [1] that, using the technology for calculating the estimate of the noise variance D_ε from the expression

$$D_\varepsilon \approx \frac{1}{N}\sum_{i=1}^{N}\left[g^2(i\Delta t) + g(i\Delta t)g((i+2)\Delta t) - 2g(i\Delta t)g((i+1)\Delta t)\right] \tag{3}$$

instead of immeasurable samples of the noise $\varepsilon(i\Delta t)$, we can determine their approximate equivalent values $\varepsilon^e(i\Delta t)$. For this purpose, formula (3) is represented in the following form:

$$D_\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\varepsilon^2(i\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} g(i\Delta t)\left[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)\right] \tag{4}$$

Due to this, taking the notation:

$$\varepsilon'(i\Delta t) = g(i\Delta t)[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)],$$

$$\operatorname{sgn}\varepsilon'(i\Delta t) = \begin{cases} +1 & when \quad \varepsilon'(i\Delta t) > 0 \\ \ \ 0 & when \quad \varepsilon'(i\Delta t) = 0, \\ -1 & when \quad \varepsilon'(i\Delta t) < 0 \end{cases} \tag{5}$$

the formula for calculating the equivalent values of samples of the noise $\varepsilon^e(i\Delta t)$ can be presented as follows:

$$\begin{aligned} \varepsilon(i\Delta t) \approx \varepsilon^e(i\Delta t) &\approx \operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|g(i\Delta t)\left[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t\right]\right|} = \\ &= \operatorname{sgn}\varepsilon'(i\Delta t)\sqrt{\left|\varepsilon'(i\Delta t)\right|}. \end{aligned} \tag{6}$$

Here, assuming that the following expression is true [1]:

$$\begin{aligned} D_\varepsilon &= \frac{1}{N}\sum_{i=1}^{N}\varepsilon^2(i\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N}\varepsilon^{e^2}(i\Delta t) = \\ &= \frac{1}{N}\sum_{i=1}^{N}\left|g(i\Delta t)\left[g(i\Delta t) + g((i+2)\Delta t) - 2g((i+1)\Delta t)\right]\right|, \end{aligned} \tag{7}$$

the formula for calculating the mean value $\bar{\varepsilon}(i\Delta t)$ of samples of the noise $\varepsilon(i\Delta t)$ can be reduced to the calculation of the mean value of the equivalent samples of the noise $\varepsilon^e(i\Delta t)$, i.e.:

$$\bar{\varepsilon}(i\Delta t) \approx \bar{\varepsilon}^e(i\Delta t) = \frac{1}{N}\sum_{i=1}^{N}\varepsilon^e(i\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N}\varepsilon(i\Delta t) \tag{8}$$

Numerous computational experiments have shown that despite possible deviations of the approximate values of the equivalent samples $\varepsilon^e(i\Delta t)$ from their true values $\varepsilon(i\Delta t)$ by the value $\Delta\varepsilon(i\Delta t) = \varepsilon^e(i\Delta t) - \varepsilon(i\Delta t)$, the following equality takes place between their estimates:

$$\begin{cases} P\left\{\frac{1}{N}\sum_{i=1}^{N}\varepsilon^{e^2}(i\Delta t) > \frac{1}{N}\sum_{i=1}^{N}\varepsilon^2(i\Delta t)\right\} \approx P\left\{\frac{1}{N}\sum_{i=1}^{N}\varepsilon^{e^2}(i\Delta t) < \frac{1}{N}\sum_{i=1}^{N}\varepsilon^2(i\Delta t)\right\} = 1 \\ P\left\{\frac{1}{N}\sum_{i=1}^{N}\varepsilon^{e}(i\Delta t) > \frac{1}{N}\sum_{i=1}^{N}\varepsilon(i\Delta t)\right\} \approx P\left\{\frac{1}{N}\sum_{i=1}^{N}\varepsilon^{e}(i\Delta t) < \frac{1}{N}\sum_{i=1}^{N}\varepsilon(i\Delta t)\right\} = 1 \end{cases}. \tag{9}$$

Both equalities (6)-(8) and our experimental research demonstrate that by means of the equivalent samples of the noise $\varepsilon^e(i\Delta t)$, we can obtain results that are identical to the results of the analysis of the same vibration signals with known real samples of the noise $\varepsilon(i\Delta t)$. To this end, we use the formula

$$X^e(i\Delta t) \approx g(i\Delta t) - \varepsilon^e(i\Delta t) \approx g(i\Delta t) - \varepsilon(i\Delta t) = X(i\Delta t) \tag{10}$$

to determine the equivalent samples $X^e(i\Delta t)$ of the useful vibration signal $X(i\Delta t)$.

In this case, it also becomes possible, by separating the equivalent noise samples $\varepsilon^e(i\Delta t)$ from the noisy vibration signal $g(i\Delta t)$ according to the obtained equivalent values of the samples of the useful signal $X^e(i\Delta t) = g(i\Delta t) - \varepsilon^e(i\Delta t)$, to determine the estimates $R^e{}_{XX}(\mu)$ and $R^e{}_{XX}(0)$ equivalent to the estimates of the correlation functions of the useful vibration signal $R_{XX}(\mu)$, i.e.,

$$R_{XX}(\mu) \approx \begin{cases} \frac{1}{N}\sum_{i=1}^{N} X^e(i\Delta t)X^e(i\Delta t) \text{ when } \mu = 0 \\ \frac{1}{N}\sum_{i=1}^{N} X^e(i\Delta t)X^e((i+\mu)\Delta t) \text{ when } \mu \neq 0 \end{cases}. \tag{11}$$

It is obvious that knowing the equivalent noise samples $\varepsilon^e(i\Delta t)$ and the useful signal $X^e(i\Delta t)$, we can determine the estimates of the cross-correlation function between the useful vibration signal $X(i\Delta t)$ and the noise $\varepsilon(i\Delta t)$ from the following expression:

$$R_{X\varepsilon}(\mu) \approx \frac{1}{N}\sum_{i=1}^{N} X(i\Delta t)\varepsilon((i+\mu)\Delta t) \approx \frac{1}{N}\sum_{i=1}^{N} X^e(i\Delta t)\varepsilon^e((i+\mu)\Delta t). \tag{12}$$

Studies also showed that despite certain errors of the samples $X_i^e(i\Delta t)$ compared with the samples of useful signals $X(i\Delta t)$, with a sufficient duration of the observation time T, equality (10) holds. Due to this, the following equality is achieved:

$$R_{XX}(\mu) \approx R_{X^eX^e}(\mu),\ R_{X\varepsilon}(\mu) \approx R_{X^e\varepsilon^e}(\mu) \tag{13}$$

which shows that, using expressions (6)-(9), using equivalent samples of the noise $\varepsilon^e(i\Delta t)$ and of the useful signal $X^e(i\Delta t)$, we can find equivalent estimates of the correlation functions $R_{X^eX^e}(\mu)$ of the useful signal and the cross-correlation function $R_{X^e\varepsilon^e}(\mu)$ between the useful signal and the noise, which allow us to solve the problem of monitoring the beginning of changes in the technical condition of the track.

4. SPECTRAL TECHNOLOGY FOR THE NOISE CONTROL OF THE BEGINNING OF CHANGES IN THE TECHNICAL CONDITION OF RAILROAD OBJECTS

As was mentioned earlier, the beginning of changes in the technical condition of the railroad track and the dynamics of their development are accompanied by the emergence of the noise correlated with the useful signal $X(i\Delta t)$. As a result, the sum noise $\varepsilon(i\Delta t)$ forms, which, in the latent period of the emergency state of the given section of the track, correlates with the useful signal.

Therefore, when solving the problem of controlling the beginning and dynamics of development of faults, it is advisable to also use estimates of the spectral characteristics of the sum noise $\varepsilon(i\Delta t)$ as informative attributes. An analysis of possible solutions to this problem showed [1] that in a spectral control of the technical condition of the track, it is advisable to replace non-measurable samples of the noise $\varepsilon(i\Delta t)$ with their approximate equivalent values $\varepsilon^e(i\Delta t)$.

Taking into account expressions (6)-(9), the formula for calculating the mean value $\bar{\varepsilon}(i\Delta t)$ of samples of the noise $\varepsilon(i\Delta t)$ can be reduced to calculating the mean value of equivalent samples of the noise $\varepsilon^e(i\Delta t)$, i.e.:

$$\bar{\varepsilon}(i\Delta t) \approx \overline{\varepsilon^e}(i\Delta t) = \frac{1}{N}\sum_{i=1}^{N}\varepsilon^e(i\Delta t). \tag{14}$$

Due to this, the expression for calculating the estimates of the spectral characteristics of the noise can be represented in the following form:

$$\begin{cases} a_{n\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e(i\Delta t)\cos n\omega(i\Delta t) \\ b_{n\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e(i\Delta t)\sin n\omega(i\Delta t) \end{cases}. \tag{15}$$

Thus, the use of algorithms (14) and (15) provides the possibility for registering the beginning of the latent period of faults, since the estimates $a_{n\varepsilon}$ and $b_{n\varepsilon}$ will differ from the reference informative attributes only at the beginning of an emergency state. Because of this, the use of these expressions will make it possible to enhance the reliability of the control of the beginning of the latent period of changes in the technical condition of the railroad track.

Studies have shown that the dynamics of development of faults in railroad objects affects the degree of correlation between the samples of the noise $\varepsilon(i\Delta t)$ and the useful signal. It affects the estimate as well as the degree of correlation between samples of the equivalent noise $\varepsilon^e(i\Delta t)$.

Due to this, based on the results of a spectral analysis of the equivalent $\varepsilon^e(i\Delta t)$ of the noise $\varepsilon(i\Delta t)$ at $\mu = 1\Delta t, 2\Delta t, 3\Delta t, ..., m\Delta t$, i.e., $\varepsilon^e((i+1)\Delta t), \varepsilon^e((i+2)\Delta t)$, $\varepsilon^e((i+3)\Delta t), ..., \varepsilon^e((i+m)\Delta t)$, it is possible to control the dynamics of an accident using the following expressions:

$$\begin{cases} a^*_{1\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e((i+1)\Delta t)\cos n\omega(i\Delta t) \\ b^*_{1\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e((i+1)\Delta t)\sin n\omega(i\Delta t) \\ a^*_{2\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e((i+2)\Delta t)\cos n\omega(i\Delta t) \\ b^*_{2\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e((i+2)\Delta t)\sin n\omega(i\Delta t) \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\ a^*_{n\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e((i+n)\Delta t)\cos n\omega(i\Delta t) \\ b^*_{n\varepsilon} \approx \dfrac{2}{N}\sum\limits_{i=1}^{N} \varepsilon^e((i+n)\Delta t)\sin n\omega(i\Delta t) \end{cases} \tag{16}$$

Then, the formula for forming the equivalent noise at $\mu = 1\Delta t$ has the following form:

$$\varepsilon^e((i+1)\Delta t) = \operatorname{sgn}\varepsilon'((i+1)\Delta t)\sqrt{g(i\Delta t)[g((i+1)\Delta t) + g((i+3)\Delta t) - 2g((i+2)\Delta t)]} \tag{17}$$

where

$$\operatorname{sgn}\varepsilon'\big((i+1)\Delta t\big) \approx \sqrt{\left|g(i\Delta t)\left[g\big((i+1)\Delta t\big) + g\big((i+3)\Delta t\big) - 2g\big((i+2)\Delta t\big)\right]\right|} \tag{18}$$

This expression at $\mu = 2\Delta t$ will take on the following form:

$$\varepsilon^e\big((i+2)\Delta t\big) = \operatorname{sgn}\varepsilon'\big((i+2)\Delta t\big)\sqrt{g(i\Delta t)\left[g\big((i+2)\Delta t\big) + 2g\big((i+4)\Delta t\big) - 2g\big((i+3)\Delta t\big)\right]} \tag{19}$$

In the general case, this expression can be written in a generalized form as follows:

$$\begin{aligned}&\varepsilon^e\big((i+\mu)\Delta t\big) = \\ &= \operatorname{sgn}\varepsilon'\big((i+\mu)\Delta t\big)\sqrt{g(i\Delta t)\left[g\big((i+\mu)\Delta t\big) + 2g\big((i+\mu+2)\Delta t\big) - 2g\big((i+\mu+1)\Delta t\big)\right]}\end{aligned} \tag{20}$$

If the fault is stable, then the estimates of the equivalent noise will repeat. However, in the presence of fault development dynamics, the estimates $a^*_{1\varepsilon}$, $b^*_{1\varepsilon}$; $a^*_{2\varepsilon}$, $b^*_{2\varepsilon}$; … ; $a^*_{n\varepsilon}$, $b^*_{n\varepsilon}$ will differ from each other over time, and in the case of high dynamics of the development of the defect degree, these differences will be significant.

5. VIBRATION NOISE-MONITORING SYSTEM

Fig. 1 shows the block diagram of a system of intelligent noise monitoring, consisting of the following modules:

1. Vibration sensor.
2. Module of sampling and formation of centered samples of the noise vibration signal $g(i\Delta t)$.
3. Module of determining the equivalent samples of the useful signal $X(i\Delta t)$.
4. Module of determining the equivalent samples of the noise $\varepsilon^e(i\Delta t)$.
5. Module of determining the equivalent estimates of the correlation functions $R_{X^eX^e}(\mu)$ of the useful vibration signal $X(i\Delta t)$.
6. Module of determining the estimates of the cross-correlation function $R_{X^e\varepsilon^e}(\mu)$ between the useful vibration signal and the noise.
7. Module of determining the spectral estimates a_{nX^e}, b_{nX^e}, $a_{n\varepsilon^e}$ and $b_{n\varepsilon^e}$ of the useful vibration signal $X(i\Delta t)$ and the noise $\varepsilon^e(i\Delta t)$.
8. Module of formation of current informative attributes consisting of current estimates $R_{X^eX^e}(\mu)$ and $R_{X^e\varepsilon^e}(\mu)$, D_ε, a_{nX^e}, b_{nX^e}, $a_{n\varepsilon^e}$ and $b_{n\varepsilon^e}$.
9. Module of formation of the set of reference informative attributes $R^{\max}_{X^eX^e}(\mu)$, $R^{\max}_{X^e\varepsilon^e}(\mu)$, $D^{\max}_{\varepsilon^e}$, $a^{\max}_{nX^e}$, $b^{\max}_{nX^e}$, $a^{\max}_{n\varepsilon^e}$ and $b^{\max}_{n\varepsilon^e}$.
10. Learning module.
11. Decision-making module.
12. Module of formation of information for signaling and remote transfer.

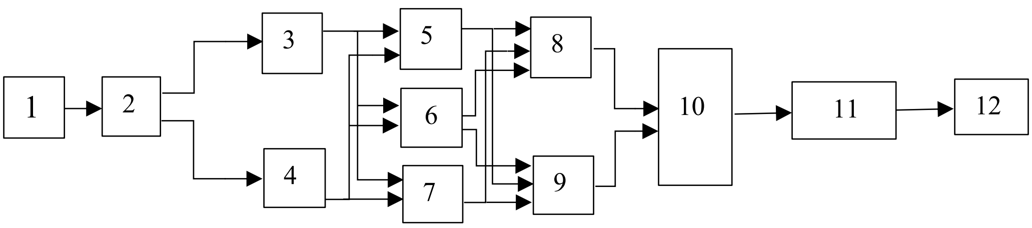

Fig. 1. Intelligent system of noise control of the technical condition of railroad tracks

As can be seen from the block diagram in Fig. 1, the track noise-monitoring system is an inexpensive and fairly simple device, which practically consists of a vibration sensor, a sampling tool and a controller. Therefore, it can be installed in any car of any train, and at the same time, does not require substantial costs.

The system operates as follows: at the beginning of the operation, the learning process begins and during the movement of the rolling stock in each control cycle, by means of the appropriate modules, the sampled vibration signal $g(i\Delta t)$ is analyzed and the obtained estimates $R_{X^eX^e}(\mu)$, $R_{X^e\varepsilon^e}(\mu)$, D_{ε^e}, a_{nX^e}, b_{nX^e}, $a_{n\varepsilon^e}$ and $b_{n\varepsilon^e}$ are saved as informative attributes. In subsequent cycles, current estimates are compared with previous estimates and only those greater than the previous maximum estimates are retained. As a result, the set W_j^e forms after a certain time, which consists of maximum estimates of informative attributes, which are formed in the current cycle. They, i.e., $R^{\max}_{X^eX^e}(\mu)$, $R^{\max}_{X^e\varepsilon^e}(\mu)$, $D^{\max}_{\varepsilon^e}$, $a^{\max}_{nX^e}$, $b^{\max}_{nX^e}$, $a^{\max}_{n\varepsilon^e}$ and $b^{\max}_{n\varepsilon^e}$, are taken as reference estimates. In the following cycles, this process repeats and similarly forms the subsequent reference set. If the current informative attributes are greater than the maximum reference attributes, then it is assumed that the training for a given haul is completed, and the comparison of current combinations of informative attributes with an element of the set of reference informative attributes begins. If the current attributes are not greater than the reference ones, then the technical condition of the track is considered unchanged. If current informative features are greater than the reference ones, it is assumed that the beginning of the latent period of changes in the technical condition of the track takes place. At the same time, information is formed in Module 12 to signal the advisability of control of the technical condition of a given haul using geometry cars. In the case when no change is detected, it is also possible to form and transmit information about the safety of the track of this haul.

6. CONCLUSIONS

Modern geometry cars, flaw detector cars and other track test cars provide reliable control of the technical condition of the railroad track in all hauls at certain intervals. Their number is limited and therefore “continuous control” of all hauls is practically impossible. Therefore, to ensure the safety of the track, they are used on schedule so that the control of each haul takes not less than a certain period of time. It is clear that the smaller this period, the greater the guarantee of safety. However, in reality, especially in seismically active regions, it is impossible to guarantee the complete stability of the technical condition of the track during these periods of time. Therefore, it is impossible to guarantee complete safety of the track. Obviously, to solve the track safety problem, it is necessary to take into account changes in the seismic situation in those time intervals in some hauls. This, in turn, requires continuous monitoring of the beginning of changes in the technical condition of the track using simple and inexpensive technical tools installed in the corresponding cars of the rolling stock. This paper considers one of the possible solutions to this problem. It is known [2-8] that by analyzing soil vibration caused by the impact of the rolling stock, it is possible to create informative attributes that can be used to determine the technical condition of the track. However, the use of traditional correlation, spectral and other analysis technologies proved to be ineffective for the creation of corresponding attributes of informative attributes by analyzing vibration signals. This is due to the fact that substantial errors caused by the effects of the noise of vibration signals arise, decreasing the adequacy of the results of track control. To eliminate this difficulty, technologies for the separate analysis of the useful vibration signal, the noise of the vibration signal and the relationship between them are proposed, and on their basis, one of the possible options for constructing intelligent technical tools of noise control is proposed, which can be easily implemented in one of the cars of all rolling stocks. The noise here is used as a carrier of diagnostic information, by means of which a set of informative attributes is formed, making it possible to identify the beginning of changes in the technical condition of the railroad bed, bridges and other railroad track objects. For instance, with a combination of known technologies, it is possible to build a hybrid noise signaling system alerting to the beginning of the latent period of changes in the technical condition, which allows exclusion of sudden destruction of large bridges and other objects of traffic arteries.

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