

METHOD FOR EXTRACTING DIAGNOSTIC FEATURES OF THE FACILITIES TECHNICAL CONDITION IN THE SYSTEM FOR MONITORING

Vladislav A. Kats, Liubov A. Adamtsevich

National Research Moscow State University of Civil Engineering, Moscow, RUSSIA

Abstract: Technical diagnostics of facilities is an urgent problem during its operation. An integral part of the implementation of diagnostic monitoring systems is the development of a decision support system (DSS) based on the analysis of acoustic emission (AE) diagnostic data and machine learning methods. A necessary condition for the application of machine learning methods in the development of DSS is the process of extracting diagnostic features from the AE signal. In the present work, an improved method is proposed for extracting diagnostic features from time series of AE signals. This includes two successive steps. At the first step, the frequency and frequency-time characteristics are calculated in a sliding window of short duration, which describe local changes in the shape and structure of single pulses. At the second step, the resulting matrix of informative features is aggregated by calculating statistical moments of various orders, which makes it possible to effectively detect long-term trends in the AE signal changes emitted by the defect. Verification of the proposed method was carried out on a full-scale control object of the oil tank RVS No. 3 ("NTEK LLC"). Based on the results obtained, a conclusion was made about the effectiveness of the proposed method in the development of diagnostic monitoring systems based on acoustic emission data.

Keywords: acoustic emission, decision support system, feature extraction, digital signal processing, feature dimension reduction.

СПОСОБ ИЗВЛЕЧЕНИЯ ДИАГНОСТИЧЕСКИХ ПРИЗНАКОВ В СИСТЕМЕ МОНИТОРИНГА ТЕХНИЧЕСКОГО СОСТОЯНИЯ СТРОИТЕЛЬНЫХ ОБЪЕКТОВ

В.А. Кац, Л.А. Адамцевич

Национальный исследовательский Московский государственный строительный университет, г. Москва, РОССИЯ

Аннотация: Техническая диагностика строительных объектов в процессе их эксплуатации является актуальной проблемой. Неотъемлемой частью реализации систем диагностического мониторинга является разработка системы поддержки принятия решения (СППР), основанной на анализе данных акустико-эмиссионной (АЭ) диагностики и методах машинного обучения. Необходимым условием применения методов машинного обучения при разработке СППР является процесс извлечения диагностических признаков из сигнала АЭ. В настоящей работе предложен улучшенный способ извлечения диагностических признаков из временных рядов АЭ-сигналов, включающий в себя два последовательных шага. На первом шаге вычисляются частотные и частотно-временные характеристики в скользящем окне малой длительности, описывающие локальные изменения формы и структуры единичных импульсов. На втором шаге полученная матрица информативных признаков агрегируется посредством расчета статистических моментов различных порядков, что позволяет эффективно детектировать долгосрочные тренды изменения сигнала АЭ, излучаемые дефектом. Верификация предложенного способа проведена на натурном объекте контроля – нефтеналивном резервуаре РВС №3 («ООО НТЭК»). На основе полученных результатов сделан вывод об эффективности предложенного способа при разработке систем диагностического мониторинга, основанных на данных акустической эмиссии.

Ключевые слова: акустическая эмиссия, система поддержки принятия решения, извлечение признаков, цифровая обработка сигнала, редукция размерности признаков.

INTRODUCTION

Diagnostics of the technical condition of facilities without its decommissioning is an urgent problem. Its solution deals with the need to continuously monitor the technical condition of building structures, develop integrated diagnostic monitoring systems, as well as effectively manage the risks of accidents at control objects. As a part of the practical implementation of the diagnostic monitoring system, an important task is to predict the failure of an object and assess the possible damage caused by an emergency situation at a construction site using the decision support system (DSS) [1].

Machine learning methods are widely used in modern DSS. It is noted that these methods promise assessing the technical condition using the data of instrumental non-destructive testing, in particular, the results of acoustic emission (AE) diagnostics [1].

A necessary condition for the use of machine learning to assess the hazard class is the extraction of a set of informative features characterizing the evolution of defects (“feature extraction”) from the registered AE signal [2]. A useful AE signal has a number of features that complicate the task of feature extraction:

a) Data from sensors (AE transducers) are usually recorded with a high sampling rate of at least 1-2 MHz, which entails a large amount of monitoring data. In this regard, of particular importance is the provision of compression of the initial data when extracting features and, on the other hand, the sensitivity of the informative features themselves to changes in the local structure of the AE time series when a single pulse of short duration appears.

b) The evolution of defects-sources of acoustic emission is slow [1].

The characteristic time for the development of defects before the onset of a pre-destructive state ranges from several weeks to several years, depending on the technical condition of a particular building structure and its operating conditions. At the same time, in order to determine the hazard class of AE source defects and to reveal the kinetics

of their evolution, it becomes necessary to register and analyze long-term trends of the corresponding informative features.

The present work proposes an improved method for extracting features from the time series of acoustic emission signals by means of sliding time windows of different widths with overlaps. This method can be used for the analysis of experimental AE time series of long duration obtained during the diagnostics of full-scale building objects.

METHODS

In this paper, we study a method for extracting diagnostic features of the defect’s presence in a structural member, based on the calculation of a number of statistical values that are directly related to the shape parameters and the local structure of the sequence of acoustic emission and noise pulses recorded during the control of the technical condition of a building structure. It is essential that the registration of noisy time series of acoustic emission in this case should be implemented in such a way that ensures the identification of the true shape of the useful AE signal against the background of noise. This condition is satisfied if recording noisy AE data using a non-threshold method [4].

At the first step, informative features in the frequency and time domains are calculated in sliding windows with overlaps in order to identify local changes in the signal shape on a small-time scale, which are associated with the occurrence of signal source defects. The length of such an analyzing window is chosen from the following considerations. On the one hand, the window length should be small enough to ensure the stationarity of the noisy signal and its spectrum within the window. On the other hand, the window length should be large enough to ensure the representativeness of the calculation of statistical features in the time domain and the required spectral resolution in the frequency domain respectively.

Based on the results of preliminary studies of experimental AE time series, it was found that the most informative on small time scales is the

following set of features in the time and frequency domains:

1) Spectral centroid.

It is defined as the weighted average amplitude of the frequency spectrum of the signal:

$$C_i = \frac{\sum_{k=1}^{W_L} kX_i(k)}{\sum_{k=1}^{W_L} X_i(k)},$$

where W_L is a number of Fourier transform coefficients

$X_i(k)$ is magnitude of k^{th} transform coefficient

i is the index of time window

The centroid is a measure of the shape of the spectrum. The growth of the centroid indicates the predominance of high-frequency components in the spectrum of the noisy signal, due to the presence of interference.

2) Range factor.

This factor describes the standard deviation of the spectrum, which is related to the width and position on the frequency axis of the signal bandwidth [6]:

$$S_i = \sqrt{\frac{\sum_{k=1}^N (k - C_i)^2 X_i(k)}{\sum_{k=1}^N X_i(k)}}.$$

Noise pulses usually have a larger peak-to-peak factor, while the appearance of AE pulses associated with a structural defect leads to a small spectral spread and a corresponding decrease in the peak-to-peak factor.

3) Spectrum attenuation factor.

This factor determines the frequency below which the q^{th} fraction of the area under the spectrum amplitude distribution function is concentrated (the corresponding frequency is analogous to the percentile in statistics [7]):

$$\sum_{k=1}^{R_i} X_i(k) = q \sum_{k=1}^N X_i(k)$$

The attenuation coefficient also describes the shape of the spectrum and can be used to differentiate the useful AE signal and noise, as well as signals related to source defects of various hazard classes.

4) Spectral flux density (sequence) of pulses.

It is defined as the square of the difference between the normalized magnitudes of the spectra of two successive time windows:

$$S_i = \sqrt{\frac{\sum_{k=1}^N (k - C_i)^2 X_i(k)}{\sum_{k=1}^N X_i(k)}}.$$

$$F_{(i,i-1)} = \sum_{k=1}^N (EN_i(k)_L - EN_{i-1}(k)_L)^2,$$

where $EN_i(k)_L = \frac{X_i(k)_L}{\sum_{m=1}^N X_i(m)_L}$,

L is the basis length of Fast Fourier Transform for spectrum calculation

This measure is sensitive to local changes in the amplitude of the spectrum associated with the dynamics of the evolution of the shape of the AE time series during the occurrence and development of AE source defects that belong to different hazard classes.

At the second step, the features calculated at the first step are aggregated over time to identify patterns of useful AE pulses due to the development of defects. Aggregation is carried out in sliding windows up to several seconds wide by averaging over a number of statistical parameters: mathematical expectation, standard deviation, median, extreme values, coefficients of variation, skewness and kurtosis.

The width of the aggregating window is chosen from the following considerations. The window length should be small enough to reveal the differences between the noise and signal components and, on the other hand, large enough to reveal the differences between the signal components of different hazard classes that arise in the process of long-term evolution of AE signal source defects.

For each averaging parameter, a time series is formed, consisting of samples, the value of each

of which is determined by a single aggregating window of a given width. Combining these series into a two-dimensional array forms a matrix of informative features. The resulting matrix is used further as input data for the application of machine learning algorithms in classifying the detected defects by hazard classes.

RESULTS AND DISCUSSION

Verification of the proposed approach was carried out on the data of experimental time series of acoustic emission obtained during the diagnostics of the technical condition of the oil tank RVS No. 3, containing defects of various hazard classes, located in the control object.

Figure 1 shows graphs of the differential distribution function of a number of informative features that describe the shape of the AE signal and its change during the transition from one hazard class of the AE source defect to another. As an example, the calculation results are shown for three features in the frequency domain - the spectral centroid and the spectral density of the AE pulse flux. In this case, the following parameters were used for the calculation on a

small-time scale (analyzing windows): the width of the sliding time window is 18 ms, the overlap is 14 ms, the width of the spectral window in calculations in the frequency domain is 32768 samples, the type of the spectral window is the Hamming weight function [6].

It follows from Figure 1 that the probability distribution densities of the statistical features listed in the previous section significantly depend on the hazard class of the AE source defect and, accordingly, on the shape of the generated acoustic emission signal: the spectral flux distribution mode (Fig. 3a) shifts towards higher values with an increase in the hazard class from the first to the third, however, the magnitude of the shift is weakly expressed. In this case, the value of the distribution density corresponding to the mode, on the contrary, increases significantly. The distribution mode of the spectral centroid (Fig. 3b) changes in the opposite way, namely, the value of the distribution density corresponding to the mode remains practically unchanged, and the mode itself noticeably shifts to the region of large values of the centroid frequency with an increase in the hazard class. At the same time, the value of the asymmetry coefficient increases.

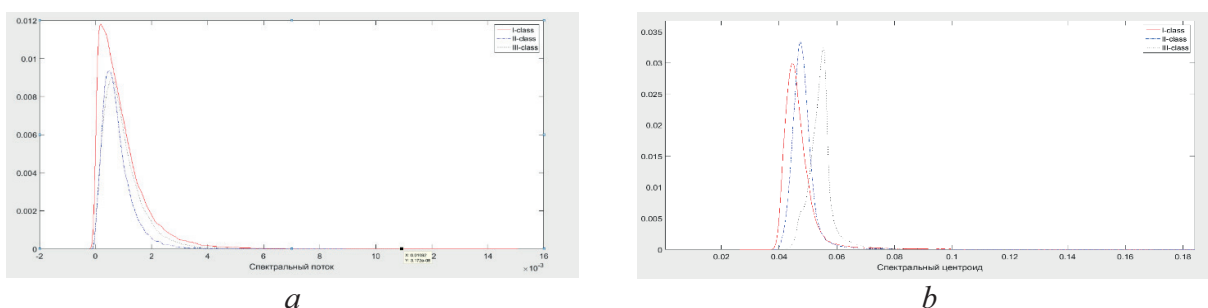


Figure 1. Probability distribution densities of statistical signs of local changes in the shape of the AE signal for defects-sources of acoustic emission of I, II, III hazard classes: a) spectral flux density; b) spectral centroid

Table 1 summarizes the results of the calculation of statistical parameters at short time intervals. From the analysis of the data presented in Table 1, it follows that the probability density of the distribution of the selected features correlates with the hazard class. Accordingly, there is reason to believe

that the time series of feature values corresponding to the obtained distribution functions can be used as input data at the second step of the proposed method, while it is advisable to use the parameters shown in Table 1 for averaging.

Table 1. Statistical values of the distribution function of diagnostic features for different hazard classes

Informative feature / distribution function parameter	Defect hazard class	Mode	Median	Skewness	Kurtosis
Spectral flux	I-class	0.0002	0.0007	2.8611	18,8905
	II-class	0.0005	0.0006	2.1951	12.4415
	III-class	0.0006	0.0008	2.3149	14.1484
Spectral centroid	I-class	0.0448	0.0452	8.5160	95.4774
	II-class	0.0473	0.0473	11.2270	176.0832
	III-class	0.0552	0.0541	9.2873	133.9230

To assess the degree of information content of the signs, a priori information about the hazard classes of AE source defects, obtained, as noted above, by an independent control method, was used. Figure 2 shows the results of feature calculation in the space of two SNE components. The points corresponding to the aggregation window, which belongs to a certain hazard class of the AE source defect, are marked in one color: green - the first class, yellow - the second, red - the third. It follows from Figure 2 that the grouping of features in the SNE-component space generally agrees with the color coding by hazard classes, while the classification error estimated using the "Accuracy" metric [14] does not exceed 2.5%. Thus, the proposed set of features and the method of its calculation make it possible to correctly divide acoustic emission signals into groups in accordance with the hazard class of AE source defects.

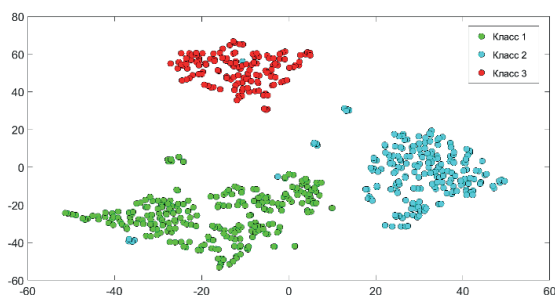


Figure 2. Averaged statistical signs of acoustic emission for the control object with sources of three hazard classes in the space of two SNE components

CONCLUSIONS

The paper presents a method for extracting diagnostic features from time series of acoustic emission signals in order to build on its basis a decision support system that provides diagnostic monitoring of the technical condition of facilities.

As diagnostic features, it is proposed to use a set of statistical parameters that are calculated in the frequency and time domains and describe the shape and local structure of the AE signal sequence: spectral centroid, flux, peak-to-peak coefficient, and spectrum attenuation coefficient.

The proposed approach was tested on a real test object - a vertical steel tank containing a defective weld. Based on a numerical comparison of the classification results in a two-dimensional feature space with a priori known from the experiment grouping of signals according to the hazard classes of AE source defects, it was found that the proposed set of features and the method of its calculation make it possible to establish a correspondence between the numerical values of the feature vector and the hazard class.

Thus, these diagnostic features can be used to describe the process of evolution of AE source defects in the control object from one hazard class to another and can be effectively used in building a decision support system as part of diagnostic monitoring systems for building structures.

REFERENCES

1. **Calabrese L., Campanella G., Proverbio E.** Noise removal by cluster analysis after long time AE corrosion monitoring of steel reinforcement in concrete // *Construction and Building Materials*. – 2012. – V. 34. – P. 362-371.
2. **Aggelis D.G.** Acoustic Emission Analysis for NDE in Concrete // *Innovative AE and NDT Techniques for On-Site Measurement of Concrete and Masonry Structures*. – 2016. – V. 20. – P. 69-88.
3. **Tzanetakis G., Cook P.** Musical genre classification of audio signals // *IEEE Transactions on Speech and Audio Processing*. - 2002. – V. 10. – P. 293–302.
4. **Kuzmin A.N., Inozemtsev V.V., Prokhorovsky A.S., Akselrod E.G., Kats V.A.** Tekhnologiya besporogovoj registracii dannyh akusticheskoy emissii pri kontrole promyshlennyh ob"ektov [Technology of non-threshold recording of acoustic emission data in the control of industrial facilities] // *Himicheskaya tekhnika*. – 2018. – No. 3. – P. 10-16. (in Russian).
5. **Inozemtsev V.V., Prokhorovsky A.S., Kuzmin A.N., Axelrod E.G.** Sposob registracii i analiza signalov akusticheskoy emissii [Method for registration and analysis of acoustic emission signals] // RF Patent No. 2570592. (in Russian).
6. **Proakis J.G., Manolakis D.K.** Digital Signal Processing. – 4 изд. – London: Pearson Education, 2009. – 1104 с.
7. **Giannakopoulos T., Pikrakis A.** Introduction to Audio Analysis - A MATLAB Approach. 2014. – Elsevier Ltd. – 262 с.
8. **Kuzmin A.N., Akselrod E.G., Kats V.A.** Akustiko-emissionnyj kontrol' pri ocenke tekhnicheskogo sostoyaniya oborudovaniya neftegazovogo kompleksa [Acoustic emission control in assessing the technical condition of the oil and gas complex equipment] // *V Mire NK*. – 2017. – V. 1 – P. 71-80. (in Russian).
9. **Moradian Z., Li B.Q.** Hit-Based Acoustic Emission Monitoring of Rock Fractures: Challenges and Solutions // *Advances in Acoustic Emission Technology*. - 2017. – V. 179. – P. 357-370.
10. **Ogura N., Yatsumoto H., Chang K.C., Shiotani T.** Development of Damage Evaluation Method for Concrete in Steel Plate-Bonded RC Slabs // *Advances in Acoustic Emission Technology*. – 2017. – V. 179. – P. 321-334.
11. **Vafa Soltangharaei, Rafal Anay, Nolan W. Hayes, Lateef Assi, Yann Le Pape, Zhongguo John Ma, Paul Ziehl.** Damage Mechanism Evaluation of Large-Scale Concrete Structures Affected by Alkali-Silica Reaction Using Acoustic Emission // *Applied Sciences*. – 2018. - №8. – P. 2148-2167.
12. **L.P. van der Maaten, Hinton G.E.** Visualizing High-Dimensional Data Using t-SNE // *Journal of Machine Learning Research*. – 2008. – V. 9. – P. 2579-2605.
13. **Barnes J., Hut P.** A hierarchical O(N log N) force-calculation algorithm // *Nature*. – 1986. – V. 324. - P. 446–449.
14. **Bishop C.M.** Pattern Recognition and Machine Learning (Information Science and Statistics). - 2 ed. - New York: Springer, 2007. - 738 p.

СПИСОК ЛИТЕРАТУРЫ

1. **Calabrese L., Campanella G., Proverbio E.** Noise removal by cluster analysis after long time AE corrosion monitoring of steel reinforcement in concrete // *Construction and Building Materials*. – 2012. – V. 34. – P. 362-371.
2. **Aggelis D.G.** Acoustic Emission Analysis for NDE in Concrete // *Innovative AE and NDT Techniques for On-Site Measurement of Concrete and Masonry Structures*. – 2016. – V. 20. – P. 69-88.
3. **Tzanetakis G., Cook P.** Musical genre classification of audio signals // *IEEE*

- Transactions on Speech and Audio Processing. – 2002. – V. 10. – P. 293–302.
4. **Кузьмин А.Н., Иноземцев В.В., Прохоровский А.С., Аксельрод Е.Г., Кац В.А.** Технология беспороговой регистрации данных акустической эмиссии при контроле промышленных объектов // Химическая техника. – 2018. – №3. - С. 10-16.
 5. **Иноземцев В.В., Прохоровский А.С., Кузьмин А.Н., Аксельрод Е.Г.** Способ регистрации и анализа сигналов акустической эмиссии // Патент РФ №2570592.
 6. **Proakis J.G., Manolakis D.K.** Digital Signal Processing. – 4 изд. – London: Pearson Education, 2009. – 1104 с.
 7. **Giannakopoulos T., Pikrakis A.** Introduction to Audio Analysis - A MATLAB Approach. 2014. – Elsevier Ltd. – 262 с.
 8. **Кузьмин А.Н., Аксельрод Е. Г., Кац В. А.** Акустико-эмиссионный контроль при оценке технического состояния оборудования нефтегазового комплекса. // В Мире НК. – 2017. – Т. 1 – С. 71-80.
 9. **Moradian Z., Li B.Q.** Hit-Based Acoustic Emission Monitoring of Rock Fractures: Challenges and Solutions // Advances in Acoustic Emission Technology. - 2017. – V. 179. – P. 357-370.
 10. **Ogura N., Yatsumoto H., Chang K.C., Shiotani T.** Development of Damage Evaluation Method for Concrete in Steel Plate-Bonded RC Slabs // Advances in Acoustic Emission Technology. – 2017. – V. 179. – P. 321-334.
 11. **Vafa Soltangharaei, Rafal Anay, Nolan W. Hayes, Lateef Assi, Yann Le Pape, Zhongguo John Ma, Paul Ziehl.** Damage Mechanism Evaluation of Large-Scale Concrete Structures Affected by Alkali-Silica Reaction Using Acoustic Emission // Applied Sciences. – 2018. - №8. – P. 2148-2167.
 12. **L.P. van der Maaten, Hinton G.E.** Visualizing High-Dimensional Data Using t-SNE // Journal of Machine Learning Research. – 2008. – V. 9. – P. 2579-2605.
 13. **Barnes J., Hut P.** A hierarchical O(N log N) force-calculation algorithm // Nature. – 1986. – V. 324. - P. 446–449.
 14. **Bishop C.M.** Pattern Recognition and Machine Learning (Information Science and Statistics). - 2 ed. - New York: Springer, 2007. - 738 p.

Vladislav A. Kats. PhD student of the department of Informational technology, systems and automatization in construction of the National Research Moscow State University of Civil Engineering; 129337, Russia, Moscow, Yaroslavskoe shosse, 26. E-mail: vladislavkats1894@gmail.com

Кац Владислав Анатольевич, аспирант кафедры Информационных систем, технологий и автоматизации в строительстве Национального исследовательского Московского государственного строительного университета, 129337, Москва, Ярославское ш., д. 26, e-mail: vladislavkats1894@gmail.com

Liubov A. Adamtsevich. Candidate of Technical Sciences, Associate Professor, Associate Professor of the department of Informational technology, systems and automatization in construction of the National Research Moscow State University of Civil Engineering; 129337, Russia, Moscow, Yaroslavskoe shosse, 26. E-mail: AdamtsevichLA@mgsu.ru.

Адамцевич Любовь Андреевна, кандидат технических наук, доцент, доцент кафедры Информационных систем, технологий и автоматизации в строительстве Национального исследовательского Московского государственного строительного университета, 129337, Москва, Ярославское ш. ,д.26; тел. +7495-287-49-14 доб. 30-42, e-mail: AdamtsevichLA@mgsu.ru; ORCID: 0000-0002-5843-0076M