Convolutional neural networks for solving problems of signal processing from segmental distributed fiber optic measuring networks

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Abstract. The work is devoted to the problem of critical situations recognition in real-time and localization of increased acoustic vibration in critical objects, based on the signals from segmental distributed fiber-optic measuring networks (DFOMN). To solve the problem, an architecture is proposed, and a model of a situational approach to using the Convolutional Neural Network as an effective classification method for processing large data arrays of the DFOMN is developed.

1. Introduction

Vibration is a common phenomenon in nature and technology, therefore, the creation of effective technologies for monitoring and analyzing the vibration processes is important - both in scientific measurements and in engineering applications. To date, a lot of various vibration sensors have already been developed, mainly based on piezoelectric, magnetostrictive, capacitive, inductive and other technologies. However, these traditional vibration sensors are highly susceptible to electromagnetic interference, which limits their applications. As a consequence, due to the need for wire lines for communication with them it is impossible to provide control of large areas. Therefore, as applications of vibration sensors are developing, there is great interest in the creation of new vibration sensors that can replace traditional sensors in order to increase their economic efficiency and immunity to electromagnetic interference. Recently, due to their low weight, elasticity, high security of signal transmission, ease of installation, corrosion resistance and immunity to electromagnetic interference, optical fibers have attracted considerable attention of researchers as a means for creating various sensors of physical quantities, long measuring lines and measuring networks, including for the creation of high-precision vibration measuring instruments [1,2]. Due to their unique features, fiber-optic monitoring systems are becoming especially attractive for use in the environments where the use of traditional sensors is limited, for example, in the marine environment or in space.

To obtain information about the status of such structures, different sensors and monitoring systems are required. One of the solutions to this problem may be the control of the spatial distribution and the level of their vibro-acoustic characteristics. As shown in [3]. Solution to the problem may be achieved by operational monitoring of the dynamic vibration pattern using the integrating fiber optic sensors. In this case, a distributed fiber-optical measuring network (DFOMN) should be used as vibration
monitoring devices. Earlier in our papers [4-6], research was conducted on the possibility of using distributed fiber optic networks for the monitoring of dynamic objects. It was shown that segmental DFOMN have a number of positive distinctive qualities, providing reconstruction of the spatial distribution of the parameters of the physical field and identifying its structural inhomogeneities in real time through the use of neural networks for computing the signal processing stage. Thus, DFOMN of segmental type may be a promising means for solving the problem of monitoring the condition of the critical objects in real time.

The aim of this work is to develop and research the methods for images recognition in real-time critical situations and localization of increased acoustic vibrations in critical objects, based on the use of segmental DFOMN, in which the signal is processed using Convolutional Neural Network - (CNN) with situational approach [7,8].

2. A situational approach to using a convolutional neural network for signal processing of segmental DFOMN

Problem statement. To recognize the situation of localization of the areas with increased acoustic vibration, we solve the problem of classification of the dynamic patterns of vibration on a critical object's surface in the following formulation. A finite set of classes is given, and there is a set of situational dynamic patterns of localization of the areas with of unacceptable bursts of acoustic disturbances, for a finite subset of which it is known to which situational class they belong. This subset is called the training sample. At the same time, the classes to which of the remaining situational dynamic patterns belong are not known. It is necessary to build an algorithm that can classify an arbitrary dynamic pattern, based on the initial set. To classify a dynamic picture means to indicate a label (or determine a situational class) to which this pattern belongs.

Let us write down the formal statement of the problem.

\[ D = \{d_1, ..., d_n\} \] is a set of descriptions for dynamic patterns of localization of the areas of unacceptable bursts of disturbances.

Each description \( d \in D \) is a sequence \( W_d = (w_1, \ldots, w_{nd}) \), where \( nd \) is the length of the description \( d \).

\[ Y = \{y_1, ..., y_m\} \] is a finite set of class labels.

\( y* : D \rightarrow Y \) is an unknown target dependence, the values of which are known only on the objects of the final training sample \( D^f = \{(d_1, y_1), \ldots, (d_n, y_n)\} \). It is required to build an algorithm \( a : D \rightarrow Y \) capable of classifying an arbitrary \( d \in D \).

Data preprocessing. In order to preprocess a large array of data coming from the DFOMN of segmental type, we will proceed from the following paradigm. The structure of the measuring network is a set of similar segments, in each of which one distributed measuring fiber-optic line is laid in the form of a "snake". Based on the multiplexed signals \( \sum_{i=1}^{m} I_i(\omega, \tau) \) from the segment, it is possible to recover the information about the amplitudes and frequencies of the signals emanating from different conventional “pixels” of the segment (the area (registration zone) of the segment with increased sensitivity to external influences effects) by demultiplexing. Thus, we collect packets of block data matrices from the segments, which arrive simultaneously at the CNN input. The CNN has been selected for processing because they are easier to train than other regular-deep neural networks, and have much less parameters to evaluate. The amplitude data in the packets of block matrices should be normalized, which will positively affect the training of the neural network. Back propagation of error is used as the CNN training method [9]. The use of the data packaging at the input will speed up the process of computations during training due to their vector-matrix representation and will allow separating the entire classification procedure by the decision maps. Each decision map has a situational class label.

A model of a convolutional neural network for classifying segmental DFOMN signals. Let us consider a situational approach to using a convolutional neural network for the classification problem based on dynamic patterns of localization of the areas with unacceptable bursts of acoustic
disturbances, which resembles the character-by-character approach for text classification proposed in [10], but has significant differences. Let us describe this approach. We call an ordered set of signal frequencies that are used in the classification the required recorded spectrum. Let \( m \) frequencies be selected. Each frequency of the spectrum is encoded using \( 1 - m \) encoding (i.e., each frequency will be associated with a vector of length \( m \), whose element is equal to the amplitude in the position equal to the ordinal number of the frequency, and to zero in all other positions). If a frequency not allocated for classification is encountered, it is represented by a code of zeros. A block data matrix is formed from the frequency-encoded signals. The dimension of the blocks in the input data matrix corresponds to the number \( l \) of conventional "pixels" and the number of allocated frequencies \( m \) for an \( N \)-dimensional segmental DFOMN. \( N \) block matrices are collected in a common package for processing. Figure 1 shows an example of the situational approach for a “two-pixel” segment and frequencies \( \omega_j \pm \delta \omega \). The example in Fig.1 shows one convolutional and one downsampling layer.

![Situational approach](image)

Fig. 1. Situational approach.

Let us describe formally an approach for processing data from one segment.

Let \( x_{ij} \) be the vector of the \( i \)-frequency and the \( j \)-th "conditional" pixel of the segment:

\[
x_{xm,j} = x_{1,j} \oplus x_{2,j} \oplus \ldots \oplus x_{m,j},
\]

where \( \oplus \) is vector assembling operation.

**Convolutional layer:**

\[
c_{i,j} = f(w \cdot x_{i-\delta+h-1,j} + b)
\]

\( c(j) = (c_{1,j}, c_{2,j}, \ldots, c_{n-h+1,j})^T \), where \( f \) is a neural network activation function; \( b \) is constant.

**MAX-pooling layer** (downsampling layer):

\[
\hat{c} = \max \{c\}.
\]

**Dropout layer** [11] (layer to reduce network overfitting):

\[
y = w(z \circ r) + b, \text{ where } \circ \text{ is element-wise multiplication; } r \text{ is a vector of zeros and ones.}
\]

Separation of data processing when determining the decision maps on signal localization can be carried out in two stages. At the first stage, processing is performed "pixel by pixel" for segments, when maps of signs of situational dynamic patterns of localization of the areas with unacceptable bursts of acoustic disturbances are generated, and at the second stage, the responses received for the packet for all \( N \) segments of the DFOMN involved in processing.

**Method for converting the situational pattern of localization of acoustic disturbance areas into a label vector of a fixed length.** To obtain a stable classification result after learning, we encode the situational classes in the form of label vectors from the set \( Y \). The label vector for each class has a
dimension $k_i = N \times n_i, i = 1, m$. We introduce the estimate of the proximity to the decision between the received vector $z'$ and the expected vector $z, z \in Z$. $Z$ is a set of decision maps after the adjustment, taking into account the dimension of the lost data $p$ for the $N$ segments. The vector $z'$ is obtained by compressing the label vector of the class $y'$. Let us define an estimate of proximity using the cosine measure of proximity (cosine similarity) of vectors by the formula:

$$similarity = \cos(\theta) = \frac{z \cdot z'}{\|z\| \|z'|} = \frac{\sum_{j=1}^{k-p} z_j \times z'_j}{\sqrt{\sum_{j=1}^{k-p} (z_j)^2} \times \sqrt{\sum_{j=1}^{k-p} (z'_j)^2}}$$

**Convolutional neural network architecture for situational approach implementation.** Let us describe the proposed CNN architecture for the situational approach (Fig. 2). Softmax is used as an activation function between the fully connected layers, and Relu is used for all other layers:

- **Relu:** $f(s) = \max(0, s)$

- **Softmax:** $f(s)_j = \frac{e^{s_j}}{\sum_{k=1}^{K} e^{s_k}}, \text{ for } j=1,\ldots, K$

![Fig. 2. CNN architecture for the situational approach.](image)

The neural network weights are initialized from normal distribution. The neural network is configured to minimize the cross-entropy loss function (logarithmic loss function - Logloss).

**Conclusion.**

The convolutional neural network with the situational approach, proposed in this paper, can be an effective classification method for processing large data sets derived from the signals of DFOMN of segmental type. This presents good opportunities for using deep learning methods for neural networks to solve relevant applied problems of decision-making for various purposes.
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