Application of system analysis methods for modeling the development of hand-arm vibration syndrome: problems and approaches to solution

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Abstract. The paper presents the approaches to the use of system analysis methods in modelling of hand-arm vibration syndrome (HAVS) in workers exposed to local vibration. The practice of using regression, information-entropy models artificial deep neural networks based on deep learning taking into account the dose of local vibration as an exposure factor is shown. The construction of HAVS occurrence model in the form of a multi-parameter regression approximated using a multilayer neural network is considered. A binary classifier that allows a set of attributes to attribute a person to a group of healthy people or to a group of people with HAVS is built. After training, the HAVS dynamics model made it possible to obtain a qualitative picture of the dependence of changes in the endocrine system on the individual experience dose of vibration and to determine the period of increased risk of pathology. The method applying to the occupational diseases differential diagnosis support system integration is discussed. Further study directions are also outlined.

1. Introduction

Hand-arm vibration syndrome (HAVS) is widespread among workers of the basic industries exposed to vibration in all industrialized countries [1]. Among all cases of occupational diseases of the working population in Russia it accounts for more than a third [2]. Currently technological solutions for the complete elimination of the vibration exposure of workers do not exist, and the organizational and technical and sanitary measures for preventing HAVS do not give tangible results. The methods such as neurological examination evaluating vibration and pain sensitivity, algesimetry, limb thermometry, electroneuromyography, radiography of the joints of the upper extremities are usually used for differential diagnosis in occupational medicine. In order to establish occupational disease, it is necessary for the worker to have prolonged contact with local vibration that exceeds the state sanitary and hygienic standard. In this case, the specific values of vibration levels and the duration of their exposure during the occupational route of the employee are not taken into account. It is very difficult for a doctor to simultaneously study multilevel data of an experimental and computational nature, which he must take into account when making a diagnosis. A predictive model that allows assessing not only the risk of developing HAVS in a particular employee, but also tracing the dynamics of the
The pathogenesis of this disease is still missing. The methods of system analysis of medical data may provide a deeper understanding of the complex functional interactions in the body of a patient, help make medical decisions. Critically evaluating traditional approaches to classification, it seems optimal to use the intellectual analysis of medical data to model the development of HAVS based on deep machine learning [3]. Its advantage is the ability of deep artificial neural networks to approximate nonlinear multi-parameter dependencies. Using mathematical modelling and data mining will allow developing a decision support system in the diagnosis of HAVS, based on the principles of personalized medicine. Doctors will receive a tool for the operational use of information about the development of the disease, its early personalized identification and scientifically based and patient-oriented medical diagnostic and preventive measures.

2. Methods and tools
The basis of the study was the information array of indicators of the functional systems of the organism of persons exposed to local vibration (healthy workers and people with HAVS), provided to the authors by specialists from the occupational diseases clinic of the East Siberian Institute of Medical and Environmental Research. The rate of excess of individual experience dose (IED) over the limit experience dose of vibration (LED) was used as an indicator of vibration exposure. IED characterizes the vibration effect for the entire work experience, takes into account the equivalent level of vibration velocity per shift and the logarithm of work experience:

$$L = L_{eq} + 10 \cdot \log \left( \frac{T}{T_o} \right)$$

where $L$ – individual experience dose of vibration, dB; $L_{eq}$ – equivalent vibration rate per shift, dB; $T$ – work experience with vibration tools, years; $T_o$ – 1 year.

The value of LED of 128 dB was determined in accordance with the maximum permissible corrected level of vibration velocity (112 dB according to the normative document SanPiN 2.2.2.540-96), the maximum value of the duration of the impact of vibration on the organism during a shift (8 hours). The work experience was limited to 40 years in models.

The study of the behaviour of regression and information-entropy of HAVS occurrence model made it possible to analyze the parameters of the functional systems of the organism depending on IED of vibration. It allowed establishing that with the growth of IED, the parameters of the thyroid system and the main activity of the brain (82.6%) made the largest contribution to the formation of HAVS [4]. In order to reduce the amount of processed data, an approach is proposed for predicting the dynamics of HAVS occurrence based on modelling changes in the integral indicators of the functioning of the endocrine system. We used three calculated universal system indexes, combining the hormones T3, T4, TTG. These indices allow making a conclusion about the state of the thyroid system – system index (SI), integral index (II) and absolute index (AI). We also used one integral pituitary-adrenal gland index (IPAI), combining hormones adrenocorticotropic hormone and cortisol, which allows considering the functional state of the pituitary-adrenal system [5,6].

We will consider the HAVS occurrence model as a formalized dependence of the change in the integral indicators of the functioning of the endocrine system on the IED, which allows identifying the critical moment of change in the indicators of the transition from a normal (healthy) state to pathology. Our interest in studying the endocrine system in HAVS is not accidental, since hormonal disorders of varying severity were noted in this disease [7]. A binary classifier, which determines the belonging to the type of healthy persons or persons with HAVS by the value of a set of indicators, can act as such a model.

We illustrate the method of classifying workers according to changes in the integral indicators of the functioning of the endocrine system in accordance with the results of clinical trials. Figure 1 shows a graph of the scatter of the normalized values of the integral indicators of the endocrine system in
persons with HAVS and healthy workers, depending on the individual length of service. It is possible to see that the differences are noticeable in the median and variance of the indicators.

![Figure 1](image.png)

**Figure 1.** Scatter of the normalized values of the integral indicators of the endocrine system in patients with HAVS and healthy workers, depending on the individual experience dose: (a) - healthy workers; (b) - persons with HAVS.

Table 1 presents information on the centers of gravity of the normalized sets of indicators for healthy workers and for persons with HAVS.

| Indices | SI  | II  | AI  | IPAI |
|---------|-----|-----|-----|------|
| Healthy Workers | 0.15 | 0.19 | 0.18 | 0.17 |
| Workers with HAVS | 0.62 | 0.64 | 0.64 | 0.61 |

Based on the existence of differences in the integral indicators of the functioning of the endocrine system, an approach to diagnosing HAVS with the help of cluster analysis is proposed.

The problem of classifying and diagnosing HAVS is the complexity of processing and searching for the mutual dependencies of multidimensional vectors of indicators of biomedical indicators by classical classification methods. Taking into the criticism of traditional classification approaches, an approach to the synthesis of the HAVS diagnostic system based on deep machine learning is proposed [8].

2.1. *Determining process roadmap*

The classification system is a deep neural network with data pre-processing.

The life cycle of the system contains two phases: settings and learning; forecasting the development of HAVS as part of an expert system (Figure 2).

On the basis of the initial information array of medical data, a number of integral indicators are formed that comprehensively characterize the state of human functional systems.

The next step is data pre-processing, where data is filtered and normalized. The resulting set of indicators is divided into two data sets. One set is used in classifier training; the other is used to control the accuracy of the classification of a working neural network.

An important step in the synthesis of the classifier is the configuration of a deep neural network and training.

After satisfactory accuracy is achieved, the classifier is ready to work as part of the HAVS expert diagnostic system.
The classifier prototype was created using the Keras and Numpy frameworks for the Python programming language. For practical implementation, the resulting configuration of the deep neural networks of the classifier should be imported into other software platforms using JSON requests. Application software that implements a decision support environment for HAVS diagnostics clones the structure of a classifier created and trained as part of research data by importing JSON data. The basic software tool for constructing a binary classifier in an application software product (expert system) is the Microsoft.ML framework.

![Image of classification system life cycle](image_url)

**Figure 2.** Classification system life cycle

### 2.2. Adapting data
The specific nature of medical research does not guarantee the completeness of the data set, and special data processing procedures are required to reduce the impact of incomplete data.

At the first stage, the data prepared for training the classifier is filtered to identify and discard pop-up values that are not consistent with the HAVS pathogenesis, obtained as input errors in the information array.

Another important problem is the presence of gaps in the time interval of indicator values. Two approaches were tested in the work:

1) replacement of missing data by the average values of indicators for the group;
2) replacement of missing data with zero values of indicators.

The second approach, in fact, is the thinning method, and in a numerical experiment this approach has significantly increased the accuracy of the classifier.

In this work, the Dropout method is used as this procedure [9, 10].

### 2.3. Building a classification system
In the synthesis of deep neural network architecture, the recommendations given in [8] were adopted. A more accurate architecture was empirically selected based on the comparison of the quality of training and the obtained accuracy of prediction. Table 2 shows the configuration of the artificial neural network of the classifier.
Table 2. Binary Classifier Configuration

| Parameters                | first layer | second layer | third layer | fourth layer |
|---------------------------|-------------|--------------|-------------|--------------|
| The number of neurons     | 10          | 500          | 100         | 2            |
| Activation Function       | -           | ReLU         | ReLU        | Softmax      |
| The number of parameters  | -           | 5500         | 55802       | 202          |

For training, a data set of 200 records (clinical observations) was used when packaging the training set of 12 records. The achieved accuracy of the prediction of classifying the subject as healthy and sick is 95.7%.

2.4. Designing diagnostic process
As a result of setting up and training the HAVS feature classification system a researcher receives a set of parameters of a deep neural network that can be transferred to an application program that implements the functions of an expert system. According to the roadmap, the attribute HAVS classifier should be a decision support tool for diagnosing HAVS by medical professionals.

In the future, it is planned to develop a Desktop application that integrates with the medical database and visualizes descriptive characteristics, as well as classifies the workers being examined according to the appearance of HAVS.

3. Results and discussion
Testing of the proposed ideas showed the possibility of classifying patients according to their membership in a group of individuals with HAVS. A classification system was created to identify the dependence of the presence of signs of HAVS on an IED.

Figure 3 shows the forecast made by the classification system for 220 workers exposure to local vibration.

In a numerical experiment, the classifier was offered a set of test data, which included two classes of objects - healthy and persons with HAVS. The ordinate axis is the probability that a person belongs to a class with HAVS, i.e. at \( p = 1 \), this is the case of the presence of HAVS. At the same time, the system ensured a forecast accuracy of 95%.

During the experiment, the classification system made it possible to obtain a qualitative picture of the transition of a person from a healthy state to a patient with HAVS.

A striking feature of the transition is a pronounced nonlinearity with inflection in the range of 4-5 times the excess of IED over LED.

3.1. Future work
Clinical studies of the functional systems of the organism of workers exposed to local vibration (healthy and persons with HAVS) revealed 50 more indicators that undergo changes with an increase in IED. Among them there are indicators characterizing the state of higher nervous activity, the central and peripheral nervous system and bioelectric activity of the brain.

The objective of further research is to expand the model of the dynamics of HAVS occurrence by including more parameters in the diagnostic model. Therefore, in the future, due to the improvement of the model, it will be possible to talk about a comprehensive, multifactorial approach to early differential diagnosis and prevention of HAVS.

At the same time, the problematic issue is the presentation of information on the results of the processing of electroencephalograms. The classification of human EEG methodology gives results in the form of expert evaluations that relate more to a qualitative form than to a quantitative one [11]. This circumstance requires a special approach when processing qualitative information, as for example in [12].
Figure 3. Modelling Results of HAVS occurrence based on IED

4. Conclusion
In this paper we have presented the results of the study, which, on the one hand, showed the possibility of successfully using system analysis methods to assess the occurrence of HAVS, and on the other, determined the further direction of work. When planning and implementing treatment and preventive measures for workers, exposure to local vibration, special medical attention should be paid to correcting their existing hormonal status disorders. At the next stage of work, it is necessary to consider the expansion of a number of medical indicators involved in modelling.

The use of mathematical modelling and data mining will allow in the future developing a decision support system in the diagnosis of HAVS, based on the principles of personalized medicine. It will contribute to the early identification of the disease, the operational use of information about its occurrence for the development of scientifically based and patient-oriented treatment, diagnostic and preventive measures.

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