PREDICTION OF PROPERTIES AND STATES OF DYNAMIC OBJECTS THROUGH ANALOGICAL INFERENCE

Yurij Kuk, Helen Lavrikova

Abstract: A technique of analogical inference for prediction of properties and states of dynamic objects the attributes which vary randomly in time is suggested. The technique is based on linear transformation of attributes of objects with the purpose to ensure the maximum probability of correct prediction of their properties and states.

Keywords: artificial intelligence, analogical inference, dynamic objects, prediction of properties.

ACM Classification Keywords: I.2.4 Artificial Intelligence: knowledge representation formalisms and methods.

Introduction

The report analyses complex multiple parameter dynamic objects, whose operation is determined by the set of attributes, which by its nature can take random values. Many such objects exist in the nature and in the human society. Functioning of economical and the environmental systems, of safety systems, complex objects of new technical equipment, etc., as a rule, depends on the behavior of a number of various attributes. Random processes, which describe the values of these attributes, determine the properties and states of the objects in study. For prediction of properties and states of dynamic objects we will apply the structure predicate model of knowledge (SPMK) [1], which represents a special type of network structure - an object - predicate net. The properties of the objects and their relations in it are described with predicates. This net represents a graph the nodes of which correspond to the objects and the predicates. Two types of objects are examined: the complex and the primary objects. Primary objects are understood as the objects that form a part of complex objects. This work examines a special case when some sets of the objects possessing a certain property act as complex objects. Let us designate such complex objects as groups. A characteristic property of each object of the set of objects of the given group is also a property of this complex object. The objects included into the into group act as the primary objects. The primary predicates are understood as the predicates indicating properties and relations of primary objects, and the predicates of complex objects are understood as the predicates indicating properties and relations of complex objects. We will divide the predicates of primary and complex objects expressing numerical characteristics of the objects into initial and derivative, that is those received as a result of mathematical transformations of the initial ones. We will divide all derivative predicates into the levels of transformation as follows. Initial predicates we will consider as the predicates of zero level of transformation. The predicates received by transformation of initial predicates, we will designate as predicates of the 1-st level of transformation. The predicates received by transformation of predicates of the 0 and 1-st levels, we will name predicates of the 2-nd level of transformation, etc. Semantic object predicate net is a four-layer graph of a pyramidal net, separate strata of which form its nodes. The first stratum P_0 corresponds to the initial predicates, indicating the properties and relations of the primary objects, and also various levels of transformation obtained basing on their derivative predicates. Elements P_0 are primary predicates. The second stratum A corresponds to the names of the primary objects. When interpreted they form subject domains of the primary predicates. The third stratum S corresponds to the names of the complex objects. In our case these are the names of the groups. The fourth stratum V are the predicates indicating the properties and relations of the complex objects, and also the derivative predicates of various levels of transformation received on their basis. In our case these are predicates which characterize various groups of objects. Elements V are the predicates of the complex objects. Their subject domains are complex objects. Curves of the lower and upper layers connect the nodes representing the objects, to the nodes, representing the predicates, and are directed from the primary and the complex objects to the predicates. They are used in interpretation of the predicates. Let ω mean the repetition factor of some predicate. Then the presence of the ω curves originating from the ω objects and converging in the given predicate, corresponds to the logical value of the predicate "true" when these objects are substituted in the predicate, and to the value "false" – in case of substitution of the object in the predicate in the absence of the curve connecting the given object to the predicate. Curves of the middle layer connect the nodes corresponding to the primary objects, to the nodes representing the complex objects. The primary elements at which the curves originate are a part of those complex objects at which these curves end. On the basis of the analysis of such object predicate net in operation, a procedure of obtaining of new knowledge about the properties and states of unknown dynamic objects through processing of experimental data is suggested . The procedure is based on measurement of distances between the predicates of the objects in study, the properties and states of which are unknown, and the predicates of groups.

Prediction of the properties of dynamic objects through analogical inference

Let us perform prediction of properties and states of dynamic objects through analogical inference, using SPMK. The inference of reasoning by analogy is the inference based on transference of reasoning from the examined area into the homomorphic area, i.e. the area somewhat similar to that examined. J groups of the objects G_1, ..., G_J of a certain subject domain will act as an examined area. Each of these groups consists of the objects possessing the characteristic specific for this group. These sets of objects form a training sample for SPMK. Available is also a set of objects - the so-called examination sample G_e. The task is to determine for each object from the set G_e one group G_j or several groups G_j, ..., G_l to which it is homomorphic. After that it is possible to draw the following inference by analogy: the given object of set G_e either possesses a property of one group G_j or totally possesses the properties of several groups G_j, ... G_l. Such inference is nothing else but some new knowledge of the object in study. It is obvious, that reliability of such knowledge requires the the further testing in practice. In the work ion we suppose, that the degree of similarity of the objects from the examination sample to the objects of the area in study is determined by the distance which is measured by means of the measure constructed in a certain way, between the attributes of the objects from the set G_e and the predicates of the objects of the groups G_1, ..., G_J. The rule of inference by analogy can be formulated as follows. Let P_1 P_2, ..., P_J be the sets of predicates of groups G_1, ... G_J, and V_1, V_2, ..., V_J correspondingly be the properties describing the objects of these groups. Let P_e be a set of predicates of some object from the set G_e. Then, if the distance between the sets of the predicates P_j and P_e: $d(P_j, P_e) < r1$, where $r1$ is a certain threshold, than $P_e \to (V_j) \wedge (\neg V_i)$, $i \neq j$ with a certain reliability $q1$, i.e. the inference is made that the object possesses property V_j and does not possess properties $V_i, i \neq j$.

Statement of a problem

Let there be a certain dynamic object which can be in one of L states. The information on the state is read with M sensors at discrete instants $t = 1,2,3,\dots$. The output of each of the sensors represents samplings of the signal amplitudes describing the states of the corresponding sector of the object in study and being the values of the time series. The task is to predict by observations of the sensors the state of a dynamic object , preliminary experimental data of observations of the sensors in different states of the dynamic object being available. To solve the problem let us act as follows. The experimental data for the time series for the i -th sensor and the l -th state of a dynamic object we will designate as $X^{(i,l)}(t)$, $i=1,\dots,M$, $l=1,\dots,L$, $t=1,2,3,\dots$. Each time series $X^{(i,l)}(t)$, containing S measurements we will divide in Z the equal cuts, containing $n=S/Z$ measurements. We will consider these informational cuts as some primary objects, of descriptions of which we will form training and examination samples. Let us select initial predicates - attributes by means of which we will describe the obtained objects. Let us designate as $s_k^{(i,j)}$ the k -th object generated from the k -th cut of time series $X^{(i,l)}(t)$. Let us examine the general case when observable cuts of the time series represent non-stationary processes. For determination of attributes of the primary objects we will act as follows. We will decompose each cut of the time series in a Fourier series: $X^{(i,l)}(t)=a_0+\sum_j[a_j\cos(\lambda_j t)+b_j\sin(\lambda_j t)]$, for $j=1,\dots,n$, $l=1,\dots,L$. Numbers λ_j are referred to as the frequencies, and the magnitudes $p_j=(a_j^2+b_j^2)*(n/2)$ - as the periodograms. Let us take as the attributes of the object $s_k^{(i,l)}$ N specific features of the function which describes the dependence of p_j on λ_j , and is referred to as the spectrogram. For example, the quantity of maxima of this function, frequency λ_j to which the maxima of the periodogram correspond, and the values of the periodograms corresponding to them. Let us designate selected attributes as $x_{1k}^{(i,l)},x_{2k}^{(i,l)},\cdots,x_{Nk}^{(i,l)}$. Depending on the state of examined dynamic object, statistical characteristics of initial attributes of the primary objects will vary. To predict the states of dynamic objects let us divide Z objects of each time series $X^{(i,l)}(t)$, $i=1,\dots M$, $l=1,\dots,L$, into K and W objects where K objects belong to the training sample, and W objects – to the examination sample. $K+W=Z$. As a result we will receive $J=M\times L$ groups of objects of the training sample:

$$G_1(l)=\{s_1^{(1,l)},s_2^{(1,l)},\cdots,s_K^{(1,l)}\},\ \dots\ G_M(l)=\{s_1^{(M,l)},s_2^{(M,l)},\cdots,s_K^{(M,l)}\},\ l=1,\dots,L\ .$$

Let us generate SPMK in which the role of the primary objects is played by the considered above cuts of the time series. Initial primary predicates of these objects are features of spectrograms of corresponding time series. As complex objects $G_1(l)$, … $G_M(l)$, $l=1,\dots,L$, let us take $J=M\times L$ groups of objects of the training sample: $G_1(l)$, … $G_M(l)$, $l=1,\dots,L$. To each node of the complex object $G_i(l)$ enters K curves from corresponding objects $s_k^{(i,l)}$, to each of which enters N curves from corresponding initial primary predicates $x_{1k}^{(i,l)},x_{2k}^{(i,l)},\cdots,x_{Nk}^{(i,l)}$. The problem consists in the following. Basing on the available experimental data obtained from all sensors to determine the state of a dynamic object, i.e. it is required to determine unknown parameter l by the sample $x_{1k}^{(i,l)},x_{2k}^{(i,l)},\cdots,x_{Nk}^{(i,l)}$, $i=1,\dots,M$. Or, in the other words, it is required to select from L sets of groups: $G_1(l)$, … $G_M(l)$, $l=1,\dots,L$, a certain single set to which the sample $x_{1k}^{(i,l)},x_{2k}^{(i,l)},\cdots,x_{Nk}^{(i,l)}$, $i=1,\dots,M$, corresponds in the best way.

Representation of knowledge about a training sample by means of SPMK

To solve a problem of prediction of the state of a dynamic object , for all objects of the SPMK by the initial primary predicates, derivative predicates of various levels of transformation are constructed. As derivative predicates of the 2-nd level of transformation let us take average values of attributes for each group of training objects. For convenience of let us put the attributes of an object $s_k^{(i,l)}$ in form of vector Euclid space R_N : $x_{1k}^{(i,l)}, x_{2k}^{(i,l)}, \cdots, x_{Nk}^{(i,l)}$, besides that when considering any l-th state of dynamic object , we will drop an index l in the formulas. Then for the group of objects $G_i = \{s_1^{(i)}, s_2^{(i)}, \cdots, s_K^{(i)}\}$ derivative predicates of the 2-nd level of transformation coincide with components of vector $h^{(i)} = (\bar{x}_1^{(i)}, \bar{x}_2^{(i)}, \cdots, \bar{x}_N^{(i)})$ the coordinates of which are equal to the component-wise average values of vectors $x_k^{(i)} = (x_{1k}^{(i)}, x_{2k}^{(i)}, \cdots, x_{Nk}^{(i)})$ of all training objects which are included into the given group:

$$\bar{x}_1^{(i)} = \frac{1}{K}\sum_{\nu=1}^{K} x_{1\nu}^{(i)}\ ,\ \bar{x}_2^{(i)} = \frac{1}{K}\sum_{\nu=1}^{K} x_{2\nu}^{(i)}\ ,\ \ldots,\ \bar{x}_N^{(i)} = \frac{1}{K}\sum_{\nu=1}^{K} x_{N\nu}^{(i)}\ .$$

Let us take as derivative predicates of the 3-rd level of transformation deviations of the values of the attributes of objects from the group averages. For the object $s_k^{(i)}$ belonging to the group of training objects $G_i = \{s_1^{(i)}, s_2^{(i)}, \cdots, s_K^{(i)}\}$, derivative predicates of the 3-rd level of transformation coincide with components of vector $\tilde{x}_k^{(i)} = (x_{1k}^{(i)} - \bar{x}_1^{(i)}, x_{2k}^{(i)} - \bar{x}_2^{(i)}, \cdots, x_{Nk}^{(i)} - \bar{x}_N^{(i)})$. As far as the states and properties of the objects in study are essentially influenceв by the existence of relations between the attributes of the object, we will take as derivative predicates of the 4-th level of transformation we will take values of relations between all pairs of the attributes of objects from every group. We will measure the value of relations by means of sample factors of a covariance. To determine the values of these derivative predicates we will introduce matrixes $A^{(1,l)}$, ..., $A^{(M,l)}$, $l = 1,\ldots,L$ the columns of which consist of deviations of the values of the attributes of objects from their group averages for corresponding groups of objects. They contain N lines and accordingly K columns and look like following:

$$A^{(1,l)} = \begin{pmatrix} x_{11}^{(1,l)} - \bar{x}_1^{(1,l)} & \cdots & x_{1K}^{(1,l)} - \bar{x}_K^{(1,l)} \\ \cdots & \cdots & \cdots \\ x_{N1}^{(1,l)} - \bar{x}_1^{(1,l)} & \cdots & x_{NK}^{(1,l)} - \bar{x}_K^{(1,l)} \end{pmatrix},\ \ldots,\ A^{(M,l)} = \begin{pmatrix} x_{11}^{(M,l)} - \bar{x}_1^{(M,l)} & \cdots & x_{1L}^{(M,l)} - \bar{x}_{lK}^{(M,l)} \\ \cdots & \cdots & \cdots \\ x_{N1}^{(M,l)} - \bar{x}_1^{(M,l)} & \cdots & x_{NL}^{(M,l)} - \bar{x}_L^{(M,l)} \end{pmatrix}$$

We form matrixes $B^{(1,l)} = A^{(1,l)} A^{(1,l)^T}$, ..., $B^{(M,l)} = A^{(M,l)} A^{(M,l)^T}$, $l = 1,\ldots,L$, where the index T indicates the operation of transposition of the matrix. They look like following:

$$B^{(1,l)} = \begin{pmatrix} \sum_{\nu=1}^{K}(x_{1\nu}^{(1,l)} - \bar{x}_1^{(1,l)})^2 & \sum_{\nu=1}^{K}(x_{1\nu}^{(1,l)} - \bar{x}_1^{(1,l)})(x_{2\nu}^{(1,l)} - \bar{x}_2^{(1,l)}) & \cdots & \sum_{\nu=1}^{K}(x_{1\nu}^{(1,l)} - \bar{x}_1^{(1,l)})(x_{N\nu}^{(1,l)} - \bar{x}_N^{(1,l)}) \\ \sum_{\nu=1}^{K}(x_{2\nu}^{(1,l)} - \bar{x}_2^{(1,l)})(x_{1\nu}^{(1,l)} - \bar{x}_1^{(1,l)}) & \sum_{\nu=1}^{K}(x_{2\nu}^{(1,l)} - \bar{x}_2^{(1,l)})^2 & \cdots & \sum_{\nu=1}^{K}(x_{2\nu}^{(1,l)} - \bar{x}_2^{(1,l)})(x_{N\nu}^{(1,l)} - \bar{x}_N^{(1,l)}) \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{\nu=1}^{K}(x_{N\nu}^{(1,l)} - \bar{x}_N^{(1,l)})(x_{1\nu}^{(1,l)} - \bar{x}_1^{(1,l)}) & \sum_{\nu=1}^{K}(x_{N\nu}^{(1,l)} - \bar{x}_N^{(1,l)})(x_{2\nu}^{(1,l)} - \bar{x}_2^{(1,l)}) & \cdots & \sum_{\nu=1}^{K}(x_{N\nu}^{(1,l)} - \bar{x}_N^{(1,l)})^2 \end{pmatrix}$$

$,\ldots,$

$$B^{(M,l)}=\begin{pmatrix} \sum_{\nu=1}^{K}(x_{1\nu}^{(M,l)}-\bar{x}_{1}^{(M,l)})^2 & \sum_{\nu=1}^{K}(x_{1\nu}^{(M,l)}-\bar{x}_{1}^{(M,l)})(x_{2\nu}^{(M,l)}-\bar{x}_{2}^{(M,l)}) & \cdots & \sum_{\nu=1}^{K}(x_{1\nu}^{(M,l)}-\bar{x}_{1}^{(M,l)})(x_{N\nu}^{(M,l)}-\bar{x}_{N}^{(M,l)}) \\ \sum_{\nu=1}^{K}(x_{2\nu}^{(M,l)}-\bar{x}_{2}^{(M,l)})(x_{1\nu}^{(M,l)}-\bar{x}_{1}^{(M,l)}) & \sum_{\nu=1}^{K}(x_{2\nu}^{(M,l)}-\bar{x}_{2}^{(M,l)})^2 & \cdots & \sum_{\nu=1}^{K}(x_{2\nu}^{(M,l)}-\bar{x}_{2}^{(M,l)})(x_{N\nu}^{(M,l)}-\bar{x}_{N}^{(M,l)}) \\ \cdots & \cdots & \cdots & \cdots \\ \sum_{\nu=1}^{K}(x_{N\nu}^{(M,l)}-\bar{x}_{N}^{(M,l)})(x_{1\nu}^{(M,l)}-\bar{x}_{1}^{(M,l)}) & \sum_{\nu=1}^{K}(x_{N\nu}^{(M,l)}-\bar{x}_{N}^{(M,l)})(x_{2\nu}^{(M,l)}-\bar{x}_{2}^{(M,l)}) & \cdots & \sum_{\nu=1}^{K}(x_{N\nu}^{(M,l)}-\bar{x}_{N}^{(M,l)})^2 \end{pmatrix}$$

To determine the value of relation between the i -th and the j -th attributes for some group of objects it is necessary to take value of the element on the intersection of the i -th line and the j -th column in the matrix of dispersion B with the upper index of the corresponding group and to divide it into the number of objects in this group, i.e. in K , then the diagonal elements will take values of sample variances of the attributes. The values of these matrixes and consequently the values of the derivative predicates of the 4-th level of transformation, without division into K , determine a mutual scatter of vectors of the attributes of the given group of objects in relation to the vector of their average values in the vector space R_N . Therefore we will call such matrixes matrixes of dispersion. Let us take values of the elements of the total matrix $B = B^{(1,1)} + \cdots + B^{(M,L)}$ as derivative predicates of the 5-th level of transformation. As the derivative predicates of the 6-th level of transformation we will take average values for each attribute of objects from the incorporated training sample, i.e. without consideration of belonging of an object to a certain group. Values of derivative predicates of the 6-th level of transformation coincide with components of the vector $h = (\bar{x}_1, \bar{x}_2, \cdots, \bar{x}_N)$, where

$$\bar{x}_1 = \frac{1}{M*L}\sum_{l=1}^{L}\sum_{i=1}^{M}\bar{x}_1^{(i,l)}\ ,\ \bar{x}_2 = \frac{1}{M*L}\sum_{l=1}^{L}\sum_{i=1}^{M}\bar{x}_2^{(i,l)}\ ,\ \ldots, \bar{x}_N = \frac{1}{M*L}\sum_{l=1}^{L}\sum_{i=1}^{M}\bar{x}_N^{(i,l)}\ .$$

As derivative predicates of the 7-th level of transformation we will take elements of matrix of dispersion for the attributes of objects from the incorporated training sample, without consideration of their belonging to a certain group. Let us designate this matrix as - W . The quantity of its elements, and consequently the quantity of such derivative predicates is N^2 .

Optimization of the net

Optimization of the net will be understood as its transformation in order to receive the optimal solution of the problem of prediction of properties and states of dynamic objects. As it was already noted, the values of the attributes of objects can be examined in form of vectors or points of the Euclidean space R_N . Vectors of attributes of objects of different groups will be mapped in this space with some sets of points which will be placed in it in a certain way. Let us put an optimization problem to find some linear transformation of vectors of attributes of objects so that for the objects with new values of attributes following two conditions will be met. Condition 1) - the points corresponding to the average values of transformed attributes for different groups of objects - the so-called centers of groups, - would be located as far as possible from each other; and condition 2) - the points corresponding to the same group of objects would be concentrated around their centers as close as possible. For solution of this problem we used the values of all derivative predicates represented in the net, besides that, the methods of linear algebra and optimization were used. The extremum was found by means of Lagrange factors. Let us take without proof the following basic theorem which allows to construct the necessary transformation.

Theorem 1. Let $B = B^{(1,1)} + \cdots + B^{(M,L)}$ be a total matrix of dispersion for separate groups, and W - be a matrix of dispersion for attributes of the incorporated training sample. Let $V = W - B$.

Then $N-1$ eigenvectors $C_1 = (c_{11},\ldots,c_{N1})$, $C_2 = (c_{12},\ldots,c_{N2})$, ..., $C_{N-1} = (c_{1,N-1},\ldots,c_{N,N-1})$ of the matrixes $VB^{(-1)}$ determine hyperplane Q, projections of vectors of attributes of objects on which met the above formulated conditions 1) and 2) of the problem of optimization.

Let's construct a hyperplane Q .with the help of the vectors $C_1 = (c_{11},\ldots,c_{N1})$, $C_2 = (c_{12},\ldots,c_{N2})$, ..., $C_{N-1} = (c_{1,N-1},\ldots,c_{N,N-1})$ found in theorem 1 Let us project N – dimensional vectors

$$x_{1k}^{(i,l)}, x_{2k}^{(i,l)}, \cdots, x_{Nk}^{(i,l)},\ k = 1,\ldots,K,\ l = 1,\ldots,L,$$

of the attributes of objects $s_k^{(i,l)}$, $k = 1,\ldots,K$, $l = 1,\ldots,L$ on it, and designate projections of these vectors as $z_k^{(i,l)} = (z_{1k}^{(i,l)},\ldots,z_{(N-1)k}^{(i,l)})$, $k = 1,\ldots,K$, $l = 1,\ldots,L$. Their dimension is equal $N-1$, and their components are equal to:

$$z_{pk}^{(i,l)} = \sum_{j=1}^{N} c_{jp} x_{jk}^{(i,l)},\ p = 1,\ldots,N-1,\ k = 1,\ldots,K.$$

Solution of problem of prediction of properties and states of dynamic objects

The linear transformation found in solution of optimization problem will transform the vectors of attributes $x_{1k}^{(i,l)}, x_{2k}^{(i,l)}, \cdots, x_{Nk}^{(i,l)}$, $l = 1,\ldots,L$ into the vector $z_k^{(i,l)} = (z_{1k}^{(i,l)},\ldots,z_{(N-1)k}^{(i,l)})$, $l = 1,\ldots,L$, lying on the hyperplane Q. For the group of objects $G_i(l) = \{s_1^{(i,l)}, s_2^{(i,l)}, \cdots, s_K^{(i,l)}\}$, $l = 1,\ldots,L$, with transformed attributes, the derivative predicates of the 2-nd level the transformations expressing the average group values of initial attributes will be transformed into the components of the vector of the center $z^{(i,l)} = (\bar{z}_1^{(i,l)}, \bar{z}_2^{(i,l)}, \cdots, \bar{z}_N^{(i,l)})$, $l = 1,\ldots,L$, for the given group of objects. These components look like following:

$$\bar{z}_1^{(i,l)} = \frac{1}{K}\sum_{\nu=1}^{K} z_{1\nu}^{(i,l)},\ \bar{z}_2^{(i,l)} = \frac{1}{K}\sum_{\nu=1}^{K} z_{2\nu}^{(i,l)},\ \ldots,\ \bar{z}_N^{(i,l)} = \frac{1}{K}\sum_{\nu=1}^{K} z_{N\nu}^{(i,l)},\ l = 1,\ldots,L.$$

We will solve the problem of prediction of properties and states of dynamic objects as follows. Let $x = (x_1, x_2, \cdots, x_N)$ be a vector of attributes of some examination object. In the 1-st step we find the projection of this vector to the hyperplane Q. As a result we receive the vector $y = (y_1, y_2, \cdots, y_{N-1})$. It components are equal to $y_p = \sum_{j=1}^{N} c_{jp} x_j$, where the factors c_{jp}, $p = 1,\ldots,N-1$, $j = 1,\ldots,N$, are components of eigenvectors

$$C_1 = (c_{11},\ldots,c_{N,1}),\ C_2 = (c_{12},\ldots,c_{N,2}),\ \ldots,\ C_{N-1} = (c_{1,N-1},\ldots,c_{N,N-1})$$

of the matrix $VB^{(-1)}$. In the 2-nd step the Euclidean distance between the vector y and all centers of groups $z^{(1,l)}$, $z^{(2,l)}$, ... $z^{(M,l)}$, $l = 1,\ldots,L$, are found. Let us designate them as $d_{1,l}$, ... $d_{M,l}$.

$$d_{i,l} = \sqrt{(y_1 - \bar{z}_1^{(i,l)})^2 + (y_1 - \bar{z}_2^{(i,l)})^2 + \cdots + (y_1 - \bar{z}_N^{(i,l)})^2},\ i = 1,\ldots,M,\ l = 1,\ldots,L.$$

We find the group to which the vector y is most close. Then we conclude by analogy, that this examination object possesses a property or a state of objects of the found group.

Problem in discernment of operating modes of the aircraft

Let's consider a problem of recognition of operating modes of helicopter with the loads of 8 and 11 tons. In solution of the problem we used the data obtained as a result of vibration meter tests of the main reducer of helicopter Ka 32N04. The data were taken from 6 sensors of the helicopter, from each of which 48000 samplings were obtained. The example of the graph of the time series, describing the first 100 samplings from the 6-th sensor for the load of 8 tons is represented on fig.1.

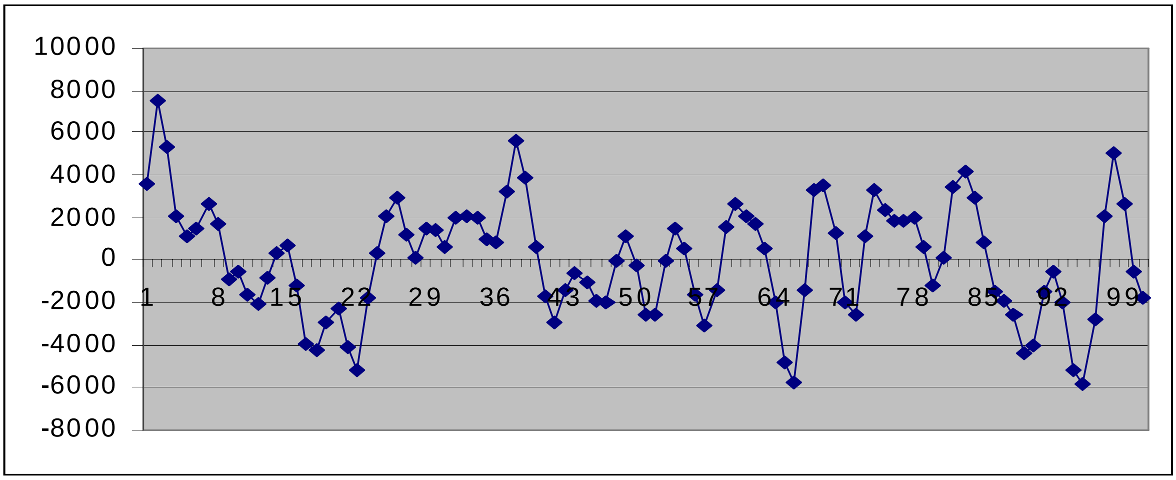

Fig.1. Time series from 6-th vibration sensor. Load of 8 tons.

It was found that for reliable recognition on the basis of load spectrograms (8 or 11 tons) readings from only one sensor are sufficient. For this work the 6-th sensor was selected.

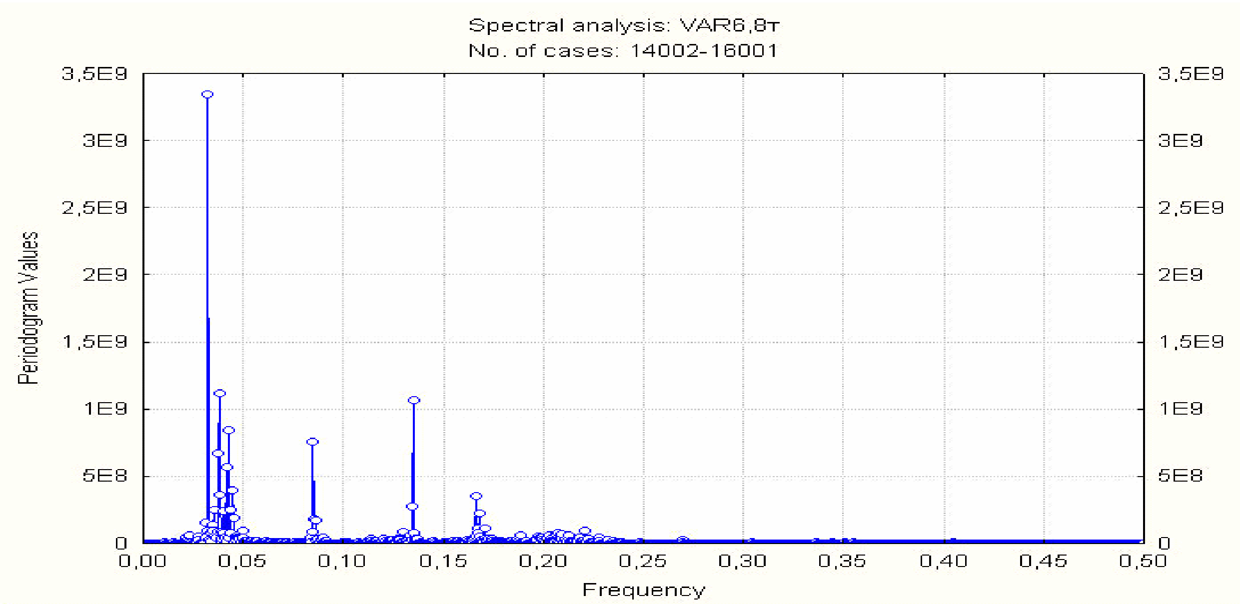

Fig.2. The typical spectrogram of time series from the 6-th vibration sensor. Load of 8 tons.

By the attributes describing prominent characteristic features of the spectrogram of the objects from the training sample, on the basis of the spectrogram of an object from the examination sample the conclusion was made about the operating mode of the helicopter. The typical spectrogram for the time series from the 6-th vibration sensor and the load of 8 tons is represented on fig. 2., and for the load of 11 tons - on fig.3.

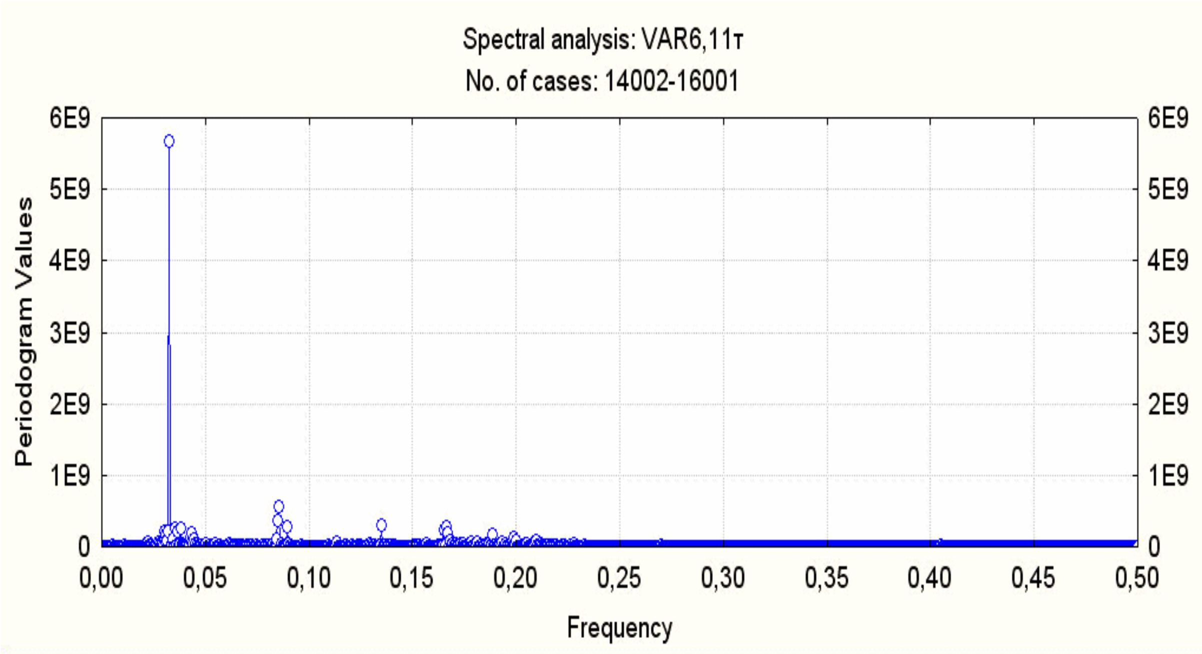

Fig. 3. The typical spectrogram of time series from the 6-th vibration sensor. Load of 11 tons.

One of the differences of the spectrogram on fig. 2 (load of 8 tons) from the spectrogram on fig. 3 (load of 11 tons) is that in the frequency interval of 0,1-0,15 there is a maximum which is essentially higher than the corresponding maximum of the spectrogram on fig. 3 in the same frequency interval. On the basis of this attribute only it is possible to determine reliably an operating mode of the helicopter.

The conclusion

The work suggests a technique of prediction of properties and states of dynamic objects, which is based on measurement of Euclidean distances between the attributes of the objects.

References

1. V.N.Koval, Yu.V.Kuk. A technique of acquisition of new knowledge in object-predicate semantic nets. // the Artificial intelligence. - 2005. - №3. - p. 25 - 36.

Authors' Information

Yurij Kuk – The Institute of Cybernetics of National Academy of Science of the Ukraine, the senior scientist, address: 40 Glushkov ave., Kiev, Ukraine; 03680; e-mail: 1913@i.com.ua

Helen Lavrikova – The Institute of Cybernetics of National Academy of Science of the Ukraine, address: 40 Glushkov ave., Kiev, Ukraine; 03680; e-mail: icdepval@ln.ua