THE PROTOTYPE OF SOFTWARE SYSTEM OF NEURAL NETWORK CONTROL OF TELEMETRY DATA

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***Abstract**: This paper describes a prototype of software system of neural network control of telemetry data for malfunction diagnosis of spacecraft subsystems. The prototype is used for testing of intelligent technologies for processing information about a spacecraft subsystems state, prediction and detection of irregularities of the spacecraft subsystem modes. The Information obtained from on-board data sources on space communication channel is used for processing.*

Keywords: neural network, telemetry, spacecraft, diagnosis.

1. INTRODUCTION

Satellite telemetry is a set of technologies that allows performing remote sensing and collection of scientific data about subject of a research (data from Earth remote sensing) and information about state of on-board spacecraft (SC) subsystems those are used by an operator of Mission Control Centers. Telemetry systems are part of command-and-measurement systems (CIS) in space industry.

Reliability and fault and contingency resiliency are important characteristics of any space system [1]. Multiple reservations of hardware and software is primary method for solving these problems, but a development of CCSDS standards [2] and a possibility to design bound hardware-software systems give an ability to dynamically redistribute control functions of Mission Control Centers and SC. This significantly increases the viability and lifetime of orbital systems.

Deterministic approach to control leads to a partial loss of diagnostic information that is contained in fluctuating component of diagnostic signals. Having a possibility of learning, artificial neural networks allow considering in diagnostics not only random nature of signals, but also features of particular spacecraft subsystems. The prototype of software system of neural network control of telemetry information (PSS-TMS) has been developed for testing neural network technologies for diagnostics of SC subsystems.

2. CONCEPTION AND ARCHITECTURE OF PSS-TMS

The following basic functional requirements have been incorporated in architecture of PSS-TMS: a solution of basic tasks of data organization and transmission, telemetry data storage, preprocessing and intelligent processing of telemetry data on spacecraft board directly.

Learning and adapting to different telemetry conditions on basis of simulation modeling is a key conceptual feature of PSS-TMS.

PSS-TMS is a set of interacting subsystems (Figure 1).

– *Interaction subsystem* provides obtaining telemetry data. It is designed to collect telemetry data from sensors, cameras, telescopes, etc., as well as information about their status, and to transfer of control commands.

– *Sensor readings analysis subsystem* performs analysis of sensor status and transmits a result of the analysis to control, diagnosis and data preprocessing subsystems.

– *Hardware diagnosis subsystem* analyzes a current state of the sensors within existing state space. It performs learning of the system and knowledge extraction about possible states of the hardware and an identification of off-nominal states on basis of current sensor states and the state space. A diagnostics result is transferred to Control subsystem.

– *Data preprocessing subsystem* performs data filtering and removing data redundancy.

– *Storage subsystem* is used to store telemetry data and descriptions of all possible states.

– *Intellectual data processing subsystem* performs neural network data processing.

– *Packets assembly subsystem* fetches the telemetry data from database (for example, HDF-files), forms data packets and transmits these ones to Data transmit/receive subsystem.

– *Control data receiving subsystem* is designed to process control data that are received from an information user and to transfer them to Control subsystem in order to form corresponding control signals.

– *Current state transferring subsystem* prepares data about the current state of the system and its sensors.

– *Data transmit/receive subsystem* provides a direct interaction with a radio channel. A transmission and a reception can be carried out through any communication channel (analog of TCP) or in form of a datagram (analog of UDP).

– *Control subsystem* is designed to collect and analyze data about state of various subsystems, as well as to generate control signals.

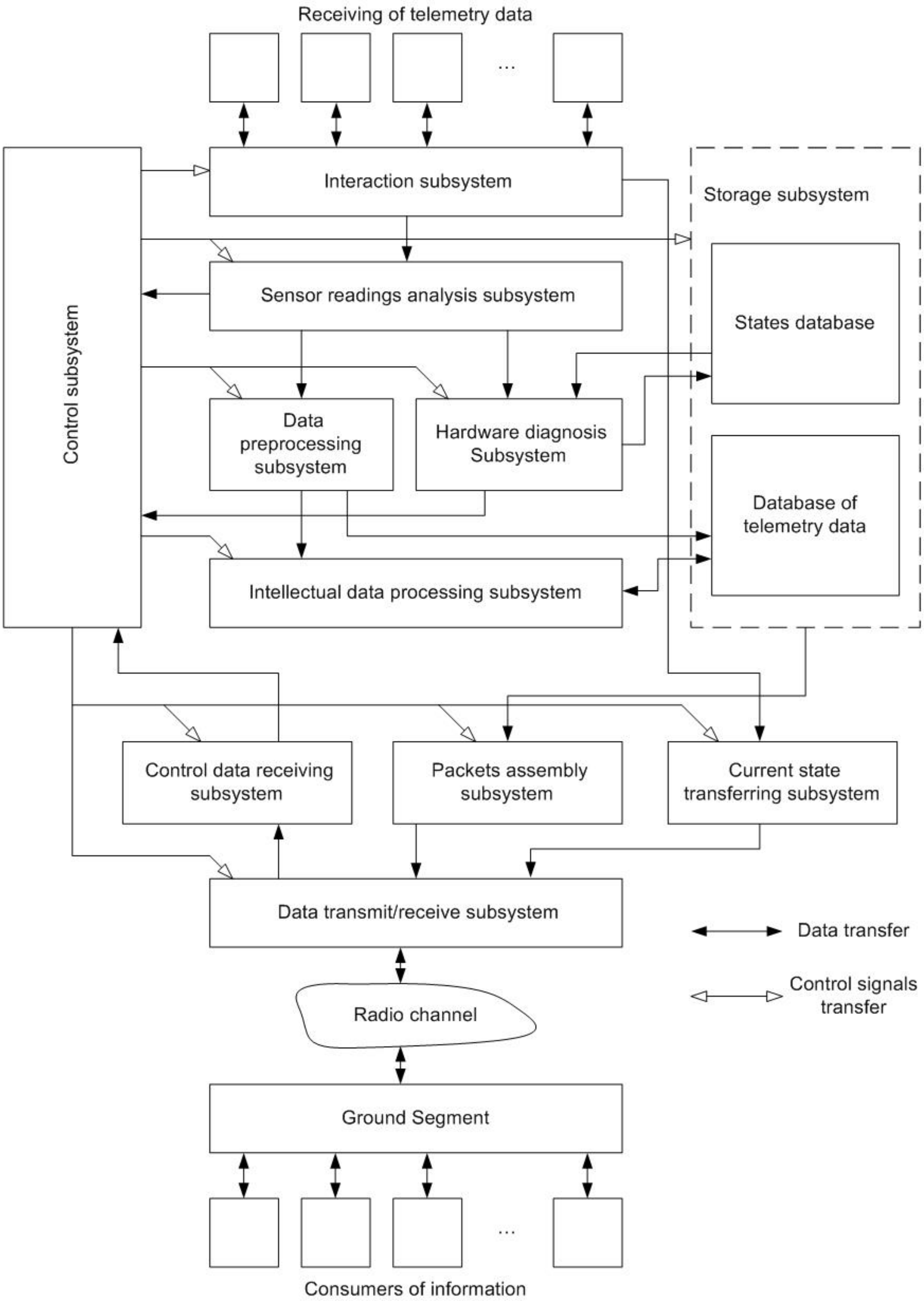


Fig. 1 - Block diagram of PSS-TMS

2. METHODS AND ALGORITHMS

2.1. Basic algorithms of telemetry data processing

Rate of change of measurable parameters is curried out on basis of estimators of the parameters in current and prior times. Filtering algorithms based on Kalman's method and multidimensional regression analysis are used.

Pedrich's algorithm of construction of membership functions of objects to the given alphabet of classes is used for suppression of data redundancy.

Various classification algorithms, including neural networks [3-11] are used for analysis of dynamic telemetry data.

2.2. Simulation modeling of measured parameters

Developing, debugging and testing of PSS-TMS software is executed on objects that emulate a nature of on-board systems and hardware signals.

Signals of temperature, pressure and vibration are the most complex for processing and analysis. Between the signals, including those ones of different physical nature, there may be a high degree of correlation.

During development of algorithms for simulation of on-board telemetry objects, we used macrophysical (thermodynamic) approach that generalizes an essence of processes occurring in airborne systems.

Various types of links between on-board objects, non-linearity of processes taking place on board and time are cause of various delayed correlations between measured parameters, which are almost impossible to describe analytically. A lot of various external factors affect significantly on the state of all SC subsystems and their objects.

2.3. The structure of neural network signal processing subsystem for prediction of the behavior of complex dynamic systems

The neural network subsystem is composed of the following functional blocks.

1) A neural network block of interpolation of SC trajectory. It performs interpolation of the trajectory and allows receiving of position and velocity vectors in intervals between measurement sessions [12].
2) A neural network block of SC trajectory prediction. It provides an extrapolation of SC trajectories.
3) A block of SC behavior prediction. It is designed for building and predicting SC phase trajectory. It allows tracing of SC in a feasible region of an attractor.
4) A neural network block for controlling SC position and orientation. It is designed to generate control actions on flywheel of SC in order to correct its motion and position.
5) A neural network telemetry data compression block. It is designed to reduce communication transmission.
6) A neural network diagnosis of SC subsystems. It is designed to monitor a performance of various SC subsystems.

An on-board telemetry is multi-dimensional time series, including these ones with a switchable dynamic. Counts of the time series characterize a state of a subject of research to certain point of time and represent them in space of measurable attributes as continuous or quasi-continuous trajectory.

It is significant for the time series generated by real dynamic objects that a transition time from one state to another is sufficiently large in comparison with a sampling period of a flow. A dynamics is not switched instantly, but there is the period of a drift from one state to another, during which the object is not located somewhere in a switching process. An apparatus of hierarchical neural network classification is proposed to solve this problem.

An algorithm for constructing hierarchical neural network classifiers (HNNC) is a process of constructing a decision tree [13], where nodes are implemented as a neural network with a specified size of a hidden layer. A construction of HNNC begins by calling an algorithm of formation of class groups (AFCG). Its result is a union of original classes into small amount of groups. Thus, a base node of HNNC (the first level of hierarchy) is formed. It is the most "coarse" classification. Resulting group of classes can be regarded as branches of the decision tree.

The neural network is created after constructing the base node for each class group (for the tree branches) and AFCG is called for each thee branch. The algorithm examines only the classes in this branch of the tree. A node of next level of hierarchy is formed as a result of AFCG, so new groups (branches) are formed. After formation of all nodes of the hierarchy level, AFCG is called for each new branch. The nodes of higher levels of the hierarchy perform more and more detailed classification.

The algorithm for constructing hierarchical neural network is stopped if the branch contains only one class, or if further detail is not possible (for example, if a percentage of classification errors exceed a certain threshold).

3. SYSTEM AND SOFTWARE ARCHITECTURE OF PSS-TMS

The software of PSS-TMS consists of PS-BOARD simulation subsystem and PS-CIS system of processing and analysis of telemetry data, which communicate through CHANNEL transport subsystem. Figure 2 shows a diagram of interaction of these subsystems with their projection on the communication levels of CCSDS [14-16].

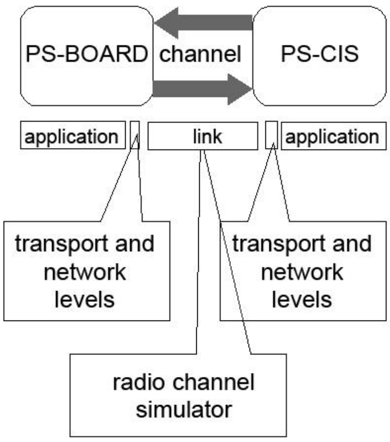


Fig. 2 - System architecture of PSS-TMS

PS-BOARD includes the following two software tools:

– simulation modeling of SC on-board systems and devices as a source of telemetry data;
– an integrated application of communication levels, which provides the minimum required level of service, which must be taken into account for proper modeling on the side of PSBOARD.
– PS-CIS includes:
– an implementation of integrated communication levels, which provides the minimum required level of service, which must be taken into account for proper modeling on the side of the PS-CIS.
– a core of PSS-TMS – a set of artificial intelligence tools based on neural network for the intelligent processing of telemetry data;
– tools for recording/playback and storage (archiving) of telemetry data.
– AIS is a standalone application in terms of the CCSDS and consists of three components: an evaluation of data, an allocation and a forecasting.
– CHANNEL includes:

– a simulation model of the radio link, which consists of the encoder and decoder of radio signal,
– tools for distortion of transmitted data.

PSS-TMS subsystems are independent components that communicate over the natural communication mechanisms, such as messages, channels and sockets. To do this, each level provides the possibility for encapsulation of packets of the current level in packets of OS communication mechanism.

4. EXAMPLES OF WORK

4.1. Evaluation of statistical characteristics of a system of quasi-stationary states

1000 synthesized three-dimensional random variables are applied to the input of the diagnostic software. A result is 18 two-dimensional vectors, which correspond to the centers of data clusters. Original data and the clusters centers are shown in Figure 3, where dots are the original data, circles are the centers of clusters.

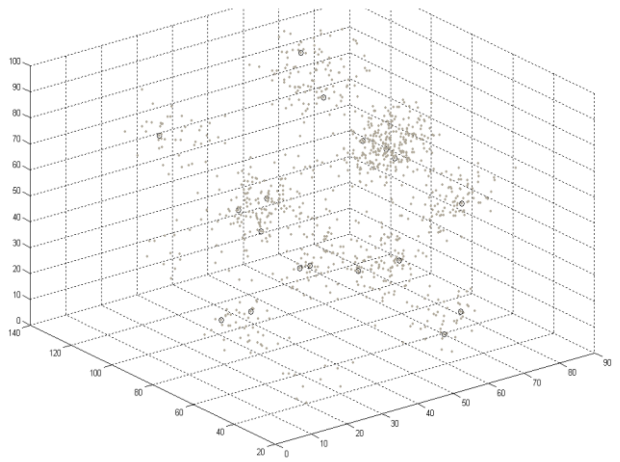


Fig. 3 - Results of tests on three-dimensional data

4.2 Classification of multi-dimensional vector

A test was conducted in the neighborhood reduction mode with the configuration file:

10
1
5
1.4

where 10 is the number of neighbors for which classification is performed; 1 is the descriptor of a reduction mode (in this case - in the neighborhood), 5 is the initial size of the neighborhood as a percentage of the field data size, 1.4 is the growth rate of neighborhood. The result of calculation is shown in Figure 4 (calculation time is 22 seconds).

4.3 The prediction of the system state

Tests were carried out on a series of two-dimensional set of vectors. The parameters defined in the configuration file have the following meanings:

30
80
1500
10000
0.1

where 30 is the memory capacity of the delay line for each detector, 80 is the number of neurons in the hidden layer, 1500 is the number of training data sets, 10000 is the maximum number of iterations of learning, 0.1 is the coefficient of learning rate.

"Power" and "noisy signal" test signals were used as test data and data for neuronetwork training. The test results are shown in Figure 5. The maximum deviation of the predicted signal from the source:

– “Power” is equal to 0.0530;
– “noisy signal” is equal to 0.2375.

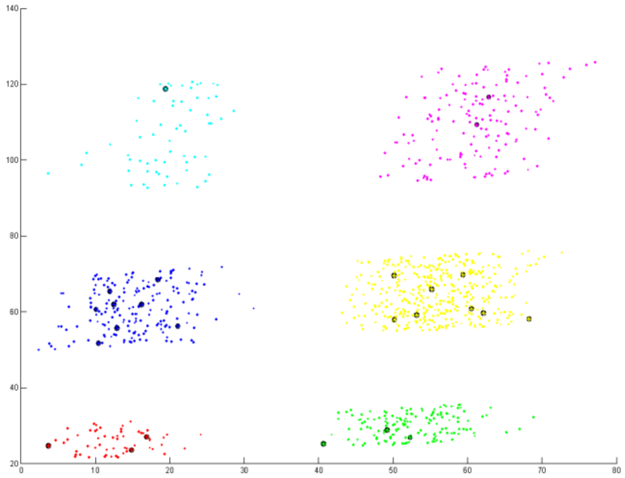


Fig. 4 - Result of the classification in the mode of reduction in the neighborhood

4.4 Prediction of multivariate time series

A prediction is based on the use of ensembles of neural networks with using elements of an evolutionary strategy for an ensemble learning algorithm [17].

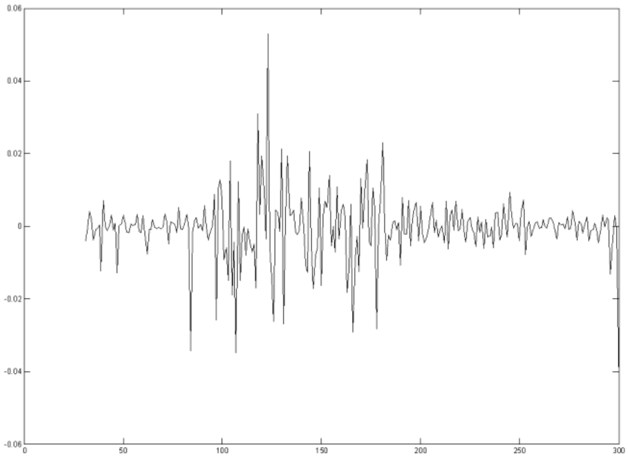
The basic version of the test data for the experiments is the telemetry data, as well as time series with different characteristics (see Table 1).

For forecasting, the data from six aircraft sensors that measure the following six parameters: a distance, a speed, a heading angle on the first line of communication, a pitching angle of the first line of communication, a heading angle on the second line of communication and a pitching angle according to the second line are used. We also used a set of «The Santa Fe Time Series Competition Data», which is synthetic generated multivariate time series of states of objects [18].

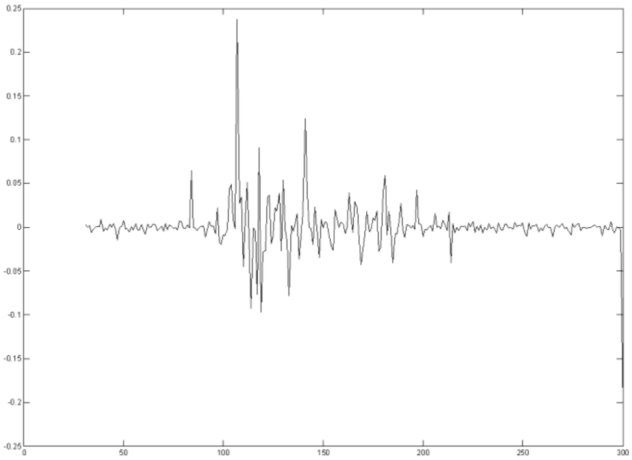
An evaluation of the model accuracy is also an important component of testing. For this purpose, a series of experiments was performed. The different single NNs, different ensembles of NNs, and the proposed model with different sets of different NN ensembles were trained on the same data. The results are shown in Table. 2: the average error on time series (Error 1), and on classified data (Error 2).

5. CONCLUSION

The developed prototype provides the intelligent processing and analysis of information about the state of the SC on-board subsystems based on neural network technology. Thus, this prototype provides the ability to automate the monitoring of SC onboard subsystems and improve its quality.



a) The prediction error according to "Power" data



b) The prediction error according to "noisy signal" data

Fig. 5 - Results of the state prediction software

Table 1. Description of data sets

Name	Description	Size
A	Generated by the laser, one-dimensional data.	1000
B1,B2,B3	data from physiological sensors, interval = 0.5s.	34000
Gen	Computer-generated multi-dimensional data of states of the objects.	28000
P39	Information from the position sensors about the state of the object in space.	2181

Table 2. Accuracy estimation

Model	Error 1, %	Error 2, %
Single NN	6,7-24	5,5-22
Assemble NN	5,6-17,2	2,7-14
The proposed model	5,6-8,3	2,7-7,7

6. REFERENCES

[1] A. Demyanov. Technology of development of aviation systems with critical security requirements. - MKA - № 3 - 2007. - PP. 84-86. [In Russian]

[2] CCSDS 650.0-B-1 Reference Model for an Open Archival Information System (OAIS). Blue Book. Issue 1. Washington, D.C.: CCSDS, September 2007.

[3] P. Zvyagin, Y. Nechayev. Neural network control of marine dynamic object / P. Zvyagin, Y. Nechayev // Neuroinformatics - 2006. Part 2. - PP. 81-87

[4] Uossermen F. neurocomputing technique. - Springer-Verlag, 1992.

[5] Zadeh L. Fuzzy logic, neural networks and soft computing / L. Zadeh // Commutation on the ASM-1994. Vol.37. №3, p.p.77-84.

[6] Behnke, S. Meter Value Recognition using Locally Connected Hierarchical Networks / S. Behnke – In Proceedings of 11th European Symposium on Artificial Neural Networks, P. 535-540, 2003.

[7] Haykin S. Adaptive Filter Theory, 4th edition. – Prentice Hall, 2002. – 936 p.

[8] Scalzo, F. Statistical learning of visual feature hierarchies / F. Scalzo, J. Piater – IEEE Workshop on Learning in CVPR, 2005.

[9] J. Bendat, A. Pirsol. Applications of correlation and spectral analysis. – M Press, 1983.

[10] Norsett, S. Solving Ordinary Differential Equations. Nonstiff Problems / Norsett, E. Hairer, G. Wanner// 2nd edition. Springer Series in Comput. Math., Vol. 8. – 1993.

[11] Hairer, E. Solving Ordinary Differential Equations II. Stiff and Differential-Algebraic Problems / Ernst Hairer, Gerhard Wanner // Springer Series in Comput. Mathematics, Vol. 14, Springer-Verlag 1991, Second revised edition 1996.

[12] Kriging-interpolation [electronic resource] - 2011. - Mode of access: http://iproc.ru/drafts/kriging/. - Date of access: 01.12.2011.

[13] I. Persiantsev. Adaptive construction of hierarchical neural network system for classification and segmentation of time series / I. Persiantsev // Lectures on Neuroinformatics, 2010. - 34 p.

[14] Spacecraft Onboard Interface Services–Subnetwork Packet Service, Draft Recommended Practice, Issue 2, CCSDS 851.0-R-2, May 2009, Current draft.

[15] Radio Frequency and Modulation Systems–Part 1: Earth Stations and Spacecraft. Recommendation for Space Data System Standards, CCSDS 401.0-B-17. Blue Book. Issue 17. Washington, D.C.: CCSDS, July 2006.

[16] «EA IFF 85» Standard for Interchange Format Files. Jerry Morrison, Electronic Arts, January 14, 1985. – http://www.martinreddy.net/gfx/2d/IFF.txt

[17] Y. Marushko. Prediction of multivariate time series using neural networks / Y. Marushko, R. Sadykhov, L. Podenok // Proceedings of the conference "Information Systems and Technology» (IST'2010). - Minsk, 2010. - S. 193-196.

[18] The Santa Fe Time Series Competition Data [Electronic resource]. – Mode of access: http://www-psych.stanford.edu/~andreas/Time-Series/SantaFe.html. – Date of access: 28.01.2012.