Advanced Techniques of Artificial Networks Design for Radio Signal Detection

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Abstract. This paper is concerned with the issue of secure radio communication of data between manned aircrafts, unmanned drones and control services. It is indicated that the use of artificial neural networks (ANN) enables correct identification of messages transmitted through radio channels and enhances identification quality by every measure. The authors designed and implemented a simulation modeling technology for ANN development, which enables signal detection with required accuracy in the context of noise jamming, natural and other types of noise.

1. Introduction

While in flight, current aircrafts use radio waves to communicate data with flight services, in particular, information about the tail number, aircraft nationality, itinerary, souls on board. Correct identification of transmitted signals in noise and jamming environment is an important practical task [1, 2].

The study of Russian and foreign scientific and technological papers [3,4] and authors’ research [5, 6] has shown that the use of artificial neural networks (ANN) enables correct interpretation of messages sent by radio channels and enhances its quality by every measure (accuracy, response speed, fail safety, reliability). Advantages of ANN over technology and algorithms of statistic radio equipment are based on a number of facts. First, ANN enables parallel recognition of arbitrary signals. Second, within ANN a problem solution does not involve breaking it down into two or more specific sub-problems. Third, advanced nano-electronic components improve performance of computer facilities 2-3 times compared to current situation [7, 8].

Like the problems they are used to solve, modern-day artificial neural systems are difficult or impossible to formalize. Due to the insufficient techniques of ANN engineering design, aspects of network performance expected at computer simulation stage significantly decline under actual operating conditions [5].

Based on the research of Russian and foreign scientific and technological works [9], it was found that today little consideration is given to the issues of ANN performance under actual operating conditions. It stems from the fact that networks’ software is supported by classic ECM with single-instruction single-data architecture and it operates at extremely reduced impact of information and physical action, which cannot be applied to most practical tasks.

The number and an impact degree of the named disturbing factors could be widely ranged. To estimate their impact on ANN performance, methods of simulation modeling (SM) could be used.
2. Methods
During simulation modeling, ANN is represented as a computer model, which assumes performance under realistic operating conditions. According to [10], the process of simulation modeling includes the following stages:

- development of analytical models for objects of data conversion (devices, signals, processes and s.o.);
- design of algorithms to simulate the data conversion process;
- software implementation of created models and algorithms, their setting, testing and operation.

The simulation modeling method for ANN development is reviewed further based on mode S signal detection by secondary surveillance radar (SSR). SSR is a primary tool of most air traffic control systems used for monitoring. Today its update includes implemented Mode S, which enables data communication uplink and downlink. While systems using Mode A/C request and receive information only in this mode, transponder Mode S enables communication in all modes including combined. Time-response characteristics of Mode S signal are given in [1].

To solve this problem, a certain approach [1, 2] suggests breaking it down into sub-problems associated with signal processing. The use of ANN enables direct identification of a signal based on samples without any additional transformations. At the same time, implemented ANN with advanced neurochips [7, 8] makes signal identification two times faster (in several cycles), which will improve performance characteristics of SSR and reduce energy consumption and hardware costs.

To create an ANN simulation model, the following models and algorithms were developed and employed:

1. Mode S signal model.
   It includes a signal selection consisting of 160 14-bit digital readings. Signal amplitude depends on aircraft distance.

2. Interference model.
   It includes models of noise, Mode S signal edge, pulse and non-synchronous interference and signals of other modes.

3. ANN model.
   Double-layer perceptron is software-implemented: number of neurons in input layer - 160, in hidden layer - 9, output layer - 1. ANN is trained using nonlinear conjugate gradient method. A training sample for ANN includes a signal for identification and extraneous signals. The desired result of ANN performance for Mode S signal is “1” and “-1” for all other cases. Aimed threshold level is established through an experiment.

   In many cases at threshold value of -0.8, the result could be interpreted as Mode S signal in noise environment or Mode S signal in non-synchronous interference environment, thus system operation accuracy is not impaired. When edge level exceeds 65% the accuracy of identification is reduced even a low threshold is applied.

4. Model system for aircraft recognition in Mode S.
   A signal sample for the entire range of vision of SSR is passed to the ANN input. The sample contains randomly grouped aircraft responses in Mode S, noises and various interferences. At ANN output, when the system identifies a signal with amplitude exceeding specified threshold value it registers a signal detection at a distance in noise environment. It then saves the reading number, passes the signal to a decoding unit and keeps analysing the sample.

5. General system modeling algorithm.
   The algorithm is given in figure 1. It consists of the following algorithms:
   - algorithm for simulation of aircraft responses;
   - algorithm for generation of training sample;
   - algorithm for system operation;
   - algorithm for evaluation of ANN performance accuracy;
   - simulation algorithm.
3. The experiment
Let us simulate a model system for aircraft recognition in Mode S with the following characteristics: the number of times the experiment is repeated – 1000; edge level - 0-100% in increments of 25%; signal-noise ratio - 8.5-19dB; detection threshold - 0.8.
Variation of probability of Mode S signal detection in noise environment with respect to a signal-noise ratio and an edge level is presented in table 1.

| Edge level | Signal-noise ratio (dB) |
|------------|-------------------------|
|            | 8.50 | 11.0 | 12.5 | 15.0 | 17.0 | 19.0 |
| 0%         | 29.0 | 83.0 | 99.9 | 99.5 | 99.9 | 99.9 |
| 25%        | 2.00 | 13.0 | 84.5 | 99.1 | 99.9 | 99.9 |
| 50%        | 1.00 | 4.00 | 38.3 | 96.1 | 99.9 | 99.9 |
| 75%        | 1.00 | 2.00 | 4.00 | 60.2 | 99.5 | 99.9 |
| 100%       | 0.00 | 0.00 | 2.00 | 8.00 | 73.5 | 99.9 |

Variation of probability of Mode S signal detection in noise environment with respect to signal-noise ratio and edge level is presented in table 1.

As seen from table 1 signal-noise enhancement has a positive impact on detection probability while an increase in signal edge level impacts it negatively.

Variation of probability of Mode S signal detection in non-synchronous interference environment with respect to signal-noise ratio and edge level is presented in table 2.

| Edge level | Signal-noise ratio (dB) |
|------------|-------------------------|
|            | 8.50 | 11.0 | 12.5 | 15.0 | 17.0 | 19.0 |
| 0%         | 30.0 | 36.1 | 31.1 | 30.4 | 39.1 | 37.4 |
| 25%        | 37.1 | 26.2 | 27.1 | 27.5 | 27.2 | 31.5 |
| 50%        | 32.0 | 21.1 | 24.5 | 29.5 | 21.1 | 34.5 |
| 75%        | 27.5 | 28.2 | 22.2 | 27.7 | 24.6 | 29.9 |
| 100%       | 26.1 | 24.5 | 24.6 | 30.1 | 27.7 | 31.3 |

As seen from table 2 probability of Mode S signal detection in non-synchronous jamming environment is about 30%. It is a rather decent result considering ANN was intentionally not trained to detect this type of noise. Non-synchronous interference appears as a result of superposition of responses from different aircrafts. Depending on superposition degree, it is possible to identify one of the responses. To enable detection of responses from two aircrafts this type of interference needs to be added to ANN training sample.

Variation of probability of extraneous signal detection with respect to a signal-noise ratio and an edge level is presented in table 3.

| Edge level | Signal-noise ratio (dB) |
|------------|-------------------------|
|            | 8.50 | 11.0 | 12.5 | 15.0 | 17.0 | 19.0 |
| 0%         | 2.00 | 2.00 | 1.00 | 0.00 | 0.00 | 1.00 |
| 25%        | 1.00 | 0.00 | 1.00 | 2.00 | 0.00 | 1.00 |
| 50%        | 0.00 | 1.00 | 3.00 | 1.00 | 1.00 | 2.00 |
| 75%        | 1.00 | 1.00 | 1.00 | 1.00 | 2.00 | 0.00 |
| 100%       | 2.00 | 2.00 | 3.00 | 2.00 | 1.00 | 2.00 |

As seen from table 3 probability of Mode S signal detection depends both on signal-noise ratio and signal edge level. Based on the experiment results, error probability does not exceed 3% in rare cases
and is most like to occur when edge level is close to 100%. Best results of detection are received at a signal-noise ratio of 15dB and more and the edge level of maximum 50%, which answers the requirements specified for the modeled system.

4. Conclusion
The authors performed ANN simulation modeling to detect Mode S signal used by SSR to obtain information about aircrafts. The use of methods of simulation modeling has allowed one to choose operational parameters for ANN (training algorithm, number of neurons) and to establish the accuracy of performance in a broad range of destabilizing factors. The information on ANN performance accuracy acquired with the help of a simulation model is necessary for functional specification of tolerances when developing the requirements for the design. A case study was used to show the perspective application of simulation modeling methods in ANN development.

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