ELINT Objects Identification Based on Intra-Pulse Modulation Classification

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ABSTRACT

The very essential functionality of electronic intelligence systems (ELINT) is the ability to automatically identify ELINT objects. In the practical operation of these systems, the results of the ELINT objects identification process are conditioned by proper analysis and measurement of their signal parameters. The more complex the signals generated by these objects, the more complex are the processes of identifying them. As the first step of the above-mentioned ELINT objects identification process in this paper, the automatic identifier is designed to automatically divide the signals of these objects into one of the four groups: without intra-pulse modulation (WO-IM), continuous frequency intra-pulse modulation (FM-IM), multiple frequency-shift keying intra-pulse modulation (MFSK-IM) and binary phase-shift keying intra-pulse modulation (BPSK-IM). Prior to this process, it was necessary to perform an appropriate pre-processing of the data corresponding to the signal of these resources. The algorithm of automatic classification based on this pre-processing with neural network using is proposed. The neural network type Pattern Recognition Network (PRN) was evaluated as the most suitable for the automatic ELINT objects classification. The results of modeling and simulations are absolutely sufficient for their practical use.

1.0 INTRODUCTION

The accurate measurement of signal source's pulse parameters in real time is very essential to determine the type and source identification in Electronic Intelligence (ELINT) systems. First, it is important to determine the primary parameters like frequency, pulse width, amplitude, direction and time of arrival of the radar signals. Subsequently, the advanced parameters like pulse modulation, frequency modulation and phase modulation can be determined. Measurement of these parameters accurately is very important, because it will help to identify two similar sources. The digital receiver is a standard solution for the modern ELINT systems. Advanced signal processing algorithms with time frequency analysis in real time to extract all the basic as well as advanced parameters of frequency and phase modulations such as chirp, barker, and poly-phase codes in addition to the pulse and continuous wave signals are described in [1]. Especially, the methods of inter-pulse, intra-pulse and intragroup modulations of modern signals are diverse and complicated. Traditional signal analyzing methods based on five conventional parameter features such as carrier frequency (f_N), time of arrival (TOA), pulse amplitude (PA), pulse width (PW) and pulse repetition interval (PRI) respectively are unsuitable to modern ELINT systems. Modern ELINT system needs to be not only intelligent, automatic, real-time, error-tolerant, also must contain equipment of learning and judgment ability. Some recognition and classification technologies based on extracted intra-impulse features are applied in [2]. Online clustering model-based algorithm using the minimum description length (MDL) criterion and algorithm based on the competitive learning for radar emitter classification are compared in [3]. To enhance the ability of specific emitter identification (SEI) to meet the requirement of modern ELINT, a novel identification approach for radar emitter signals based on type-2 fuzzy classifier is presented in [4]. Based on the ELINT feature extraction of radar emitter signals, the type-2 fuzzy classifier is applied to identification of radar emitters. An overview of the methods of measurement emitter signal features parameters in the time and the frequency domain is provided in [5]. More advanced recognition methods, which may recognize particular copies of radars of the same type, are called identification. The comparison of Hierarchical Agglomerative Clustering Algorithm (HACA) based on Generalized Agglomerative Scheme (GAS) with other SEI methods is implemented in [6]. The Signal-to-Noise-Ratio (SNR) is one of the fundamental limits to what can be learned about a signal through ELINT [7]. This problem and the statistical techniques used in ELINT are briefly discussed in [8]. The role of knowledge-based processing methods and how they may be applied to the key ELINT/ESM signal processing functions of deinterleaving, merge and emitter identification is discussed in [9]. One of the methods of recognizing the radar pulse signal in ELINT/ESM is proposed in [10]. This method recognizes the PRI modulation types using classifiers based on the property of the autocorrelation of the PRI sequences for each PRI modulation type.

During the last years we have observed fast development of the electronic devices and ELINT systems. Simultaneously, utilization of some tools of artificial intelligence (AI) during the process of emitter identification is discussed too. The process of SEI based on extraction of distinctive radiated emission features by specific database (DB) for identifying a detectable radar emission is presented in [11]. A neural network (NN) in many variations as kind of AI is proposed for classification of radar pulses in autonomous ESM systems standardly [12],[13]. After performing the principal component analysis (PCA), the hidden layer neurons of the NN have been modelled by considering intra-class discriminating characteristics of the training images. This helps the NN to acquire wide variations in the lower-dimensional input space and improves its generalization capabilities. The neural networks and support vector machines are adopted to design classifiers to identify the signal parameters automatically. The fuzzy NN is used to classify streams of pulses according to radar type using their functional parameters [14].

The aim of this work is classification and identification of ELINT objects which use any kind of intra-pulse modulation. As the first step of the identification process, the automatic dividing the signals of these objects into one of the four groups is proposed: without intra-pulse modulation (WO-IM), continuous frequency intra-pulse modulation (FM-IM), multiple frequency-shift keying intra-pulse modulation (MFSK-IM) and binary phase-shift keying intra-pulse modulation (BPSK-IM). Prior to this process, it was necessary to perform an appropriate pre-processing of the data corresponding to the signal of these resources. The algorithm of automatic classification based on this pre-processing with neural network using is proposed.

2.0 ELINT SIGNALS

The possibilities of generating different types of complex signals by ELINT objects are growing up with the development of microwave and digital technologies. The more complex the signals generated by these objects, the more complex are the processes of identifying them. At present, it is possible to divide up the modern ELINT signals into the following groups:

1. Radio pulses without intra-pulse modulation (WO-IM), i.e. signals with constant amplitude, frequency and phase, the behavior of which in time domain can be described by the following equation:

$$s(t) = \begin{cases} A[\sin(\omega t + \varphi)] + N(t) & \text{for } t \in \langle i.PRI, i.PRI + PW), \\ N(t) & \text{for } t \in \langle i.PRI + PW, i.PRI + PW + DT) \end{cases} \tag{1}$$

   where A is a signal amplitude, ω is an angle frequency, PRI is a pulse repetition interval, PW is a pulse width, DT is a dwell time, φ is initial phase, $N(t)$ is a Gaussian noise and $i = 0, 1, 2, \ldots I$ is an integer.

2. Radio pulses with continuous frequency intra-pulse modulation (FM-IM), i.e. constant amplitude and phase and variable frequency signals. Frequency changes may be linear (LFM-IM) or non-linear (NLFM-IM), with frequency increasing or decreasing. The behavior of LFM-IM signals in time domain

can be described by the following equation:

$$s(t)=\begin{cases} A\left[\sin\left(\omega t+\Delta\omega\dfrac{t^2}{PW}\right)\right]+N(t) & \text{for } t\in\langle i.PRI, i.PRI+PW\rangle, \\ N(t) & \text{for } t\in\langle i.PRI+PW, i.PRI+PW+DT\rangle \end{cases} \tag{2}$$

where $\Delta\omega$ is an angle frequency deviation. The behavior of NLFM-IM signals in time domain can be described by the following equation:

$$s(t)=\begin{cases} A\left[\sin\left(\omega t+\Delta\omega\dfrac{t^3}{PW}\right)\right]+N(t) & \text{for } t\in\langle i.PRI, i.PRI+PW\rangle, \\ N(t) & \text{for } t\in\langle i.PRI+PW, i.PRI+PW+DT\rangle. \end{cases} \tag{3}$$

3. Radio pulses with multiple frequency-shift keying intra-pulse modulation (MFSK-IM), i.e. constant amplitude and phase signals with variable frequencies, the behavior of which in time domain can be described by the following equation:

$$s(t)=\begin{cases} A[\sin(\omega_m t+\varphi)]+N(t) & \text{for } t\in\langle i.PRI, i.PRI+PW\rangle, \\ N(t) & \text{for } t\in\langle i.PRI+PW, i.PRI+PW+DT\rangle \end{cases} \tag{4}$$

where ω_m is a signal angle frequency used in a subpulse.

4. Radio pulses with binary phase-shift keying intra-pulse modulation (BPSK-IM), i.e. constant amplitude and frequency signals with variable phase, the behavior of which in time domain can be described by the following equation:

$$s(t)=\begin{cases} A[\sin(\omega t+\Delta\psi_m)]+N(t) & \text{for } t\in\langle i.PRI, i.PRI+PW\rangle, \\ N(t) & \text{for } t\in\langle i.PRI+PW, i.PRI+PW+DT\rangle \end{cases} \tag{5}$$

where $\Delta\psi_m$ is a phase deviation in *m-th* subpulse, which in the case of BPSK reach the value 0 for modulation signal equals +1 and value π for modulation signal equals -1.

A presentation of all above mentioned ELINT signals in time domain without noise are shown in Figure 1.

The very essential functionality of ELINT systems is the ability to automatically identify ELINT objects. In the practical operation of these systems, the results of the ELINT objects identification process are conditioned by proper analysis and measurement of their signal parameters. Parameter analysis and measurements are mostly performed in time, frequency or in time-frequency domain. In this way, the so-called descriptors are obtained, whose values are characteristics for each type of ELINT objects and are used to identify them. The basic types of these descriptors include carrier frequency f_N, pulse repetition interval PRI and pulse width PW.

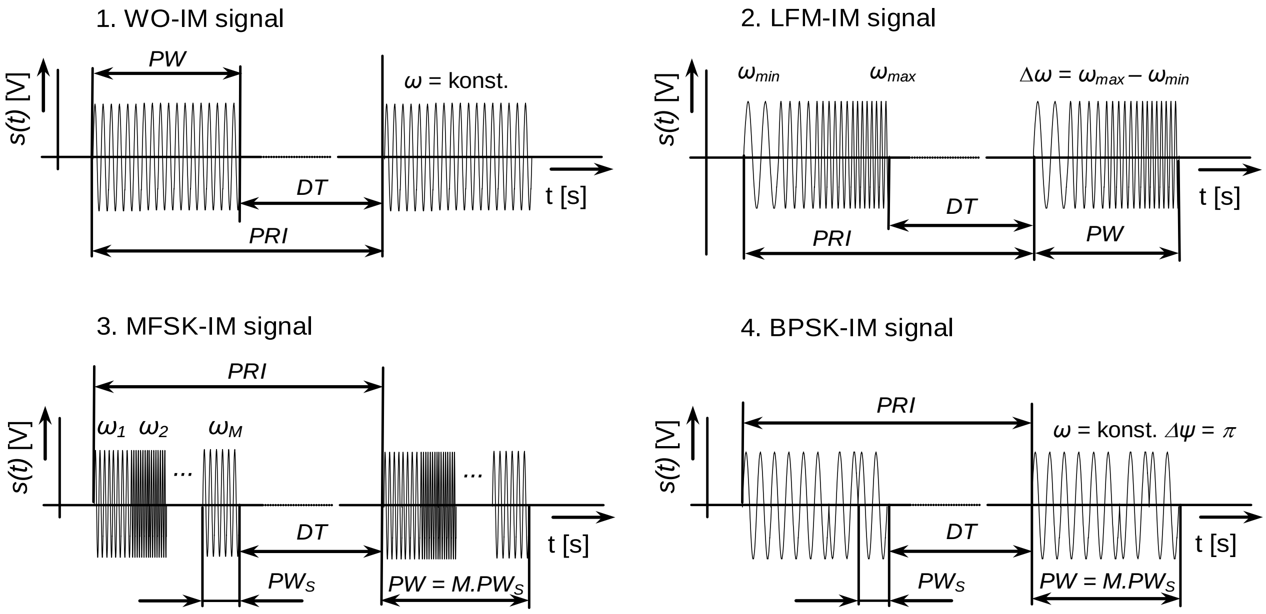

Figure 1: Types of ELINT signals in time domain without additive noise.

As mentioned above, with the development of microwave and digital technologies, the possibilities of generating different types of complex signals also grow. In this regard, additional descriptors are defined in the ELINT objects identification process, which are characteristic of only some types of signals, i.e. some ELINT objects. Therefore, it is necessary to process the individual signal types (groups of signals) separately. Emphasis is placed not only on the measurement of basic descriptors but also on the correct extraction of further (specific) descriptors of these signals. Specific descriptors include e.g. frequency deviation and frequency changes slope of FM-IM signals, subpulse width, frequency values for every subpulse, subpulses sequence for MFSK-IM signals, and subpulse width and code sequence for BPSK-IM signals.

The principle of the work of most modern ELINT systems is based on the involvement of so called software defined receivers with sampling at the intermediate frequency. Since the processing of signals in these devices is predominantly in digital form, the use of different methods of digital data processing is also envisaged in the process of identifying ELINT objects. The key issue in the ELINT objects identification process is then to design and program a generally robust algorithm to ensure proper preprocessing and processing of data for neural network or database systems.

3.0 STRUCTURE OF AUTOMATIC IDENTIFICATION SYSTEM

In this part of the paper, attention is paid to the classification part design of the automatic ELINT objects identification system. From a qualitative point of view, it is possible to divide the ELINT objects identification process into the next three stages:

1. Objects classification,
2. Object type recognition,
3. Object mode recognition.

Based on the experiments and practical experience from the signal and data processing, the authors proposed a two-stage automatic ELINT objects identification system, whose structural diagram is shown in Figure 2.

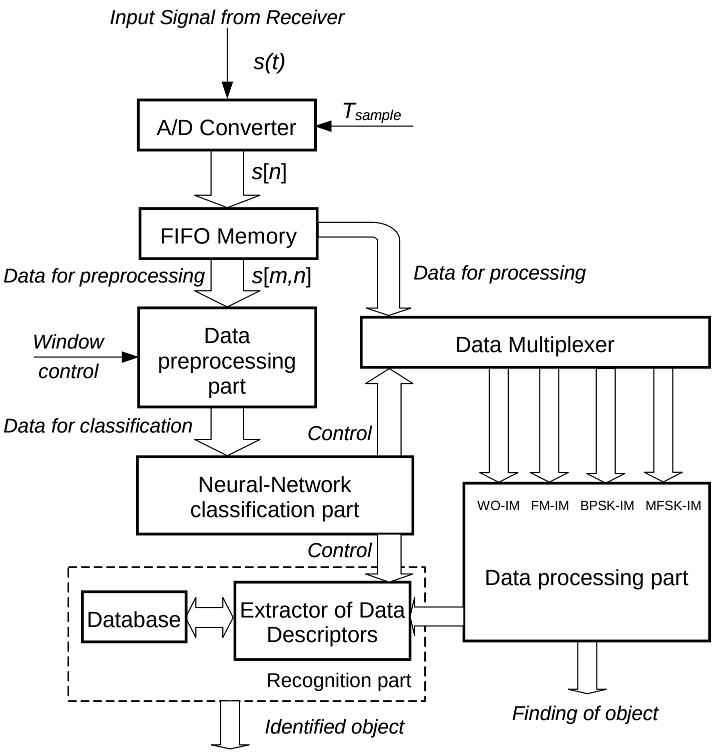

Figure 2: Structural schema – two-stage automatic ELINT objects identification system.

The input of the automatic identification system consists of an A/D converter and a FIFO memory where sampled signals are stored in a data matrix in the shape

$$S[M,N]=\begin{bmatrix} s[1,N] \\ s[2,N] \\ \vdots \\ s[M,N] \end{bmatrix}=\begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1N} \\ s_{21} & s_{22} & \cdots & s_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{MN} \end{bmatrix}, \tag{6}$$

where m = 1, 2 … M is the number of received signal periods and n = 1, 2 … N is number of samples per reception period.

The output of FIFO memory is connected to the data preprocessing part (the operation will be explained in Section 3) and to the data multiplexer. Preprocessed data proceeds to an automated NN-based classifier which controls both data multiplexer and database as a segment of recognition part. Based on classification results, data multiplexer switches individual data into their corresponding data processing part. On this place, the measurement and analysis of the corresponding signal descriptors (parameters) are compared with the data specified in the database using the extractor of data descriptors (EDD). The outcome of the proposed automatic identification system is the object type recognition or object mode recognition. In the next part of the paper, attention will be paid to the process of data pre-processing and automatic classification of ELINT objects using neural network.

4.0 CLASSIFICATION OF ELINT OBJECTS USING NEURAL NETWORK

In the first step of the above-mentioned ELINT objects identification process, the automatic identifier is designed to automatically divide the signals of these objects into one of the four groups (WO-IM, FM-IM, MFSK-IM or BPSK-IM), i.e. their automatic classification is realized. However, prior to this process of ELINT objects classification, it was necessary to perform an appropriate pre-processing of the data corresponding to the signal of these resources. This ensured the quality requirements for their automatic classification. At the same time as the algorithm for data pre-processing was verified, the selection of the appropriate type and robustness of the neural network was performed. Structural schema of preprocessing and classification part is shown in Figure 3.

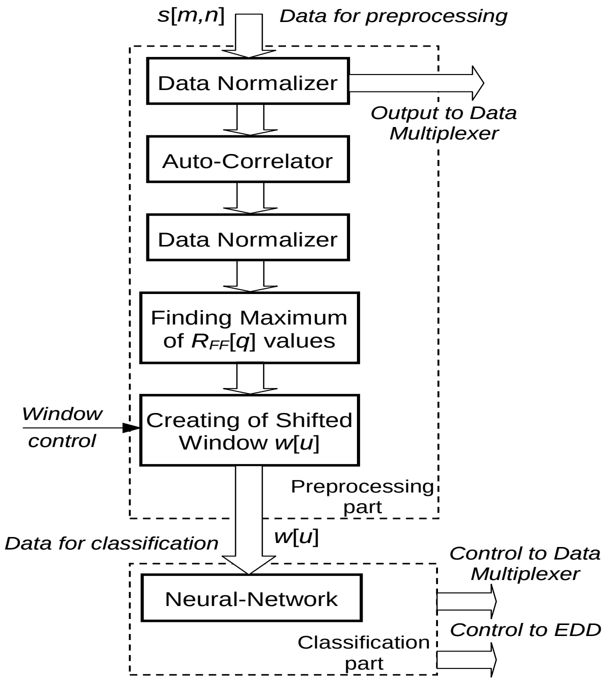

Figure 3: Structural schema of preprocessing and classification part.

The data from the data matrix for each row enters to the input of preprocessing part. Each row is normalized according to the amplitude, and then for this line the autocorrelation function is calculated according to the equation:

$$R_{XX}[q] = \sum_{n=0}^{N-q-1} (s[n+1])(s[n+q+1])^{*}, \tag{7}$$

where q is a sequence index of autocorrelation function, $s[n]$ is a data signal and * represents the complex conjugate. Consequently, in the sense of the equation

$$R_{XX}[q] = \frac{R_{XX}[q]}{\max(R_{XX}[q])} \tag{8}$$

performs the normalization of the autocorrelation function, determines the position of its maximum value pos_{max} and corresponding number of samples of the descending part of the autocorrelation function is selected by the windowing function *w[u]*. For expressing the windowing function *w[u]* is valid the equation:

$$w[u] = \langle R[pos_{\max} + v] : R[pos_{\max} + v + (u-1)] \rangle \tag{9}$$

where u is a number of samples of windowing function (window size) and v is number of first sample to perform windowing function from all samples of autocorrelation function (window shift). After this step, each row from data matrix is normalized according to number of samples.

Window size value of windowing function *w[u]* was optimized during the simulations and the value 4096 samples seems to be optimal with respect to the quality of results and the classification time. So called *normalized function* is product of windowing function for every mentioned group (WO-IM, FM-IM, MFSK-IM and BPSK-IM). A presentation of the normalized function examples for every single group of ELINT signals used in classification are shown in Figure 4.

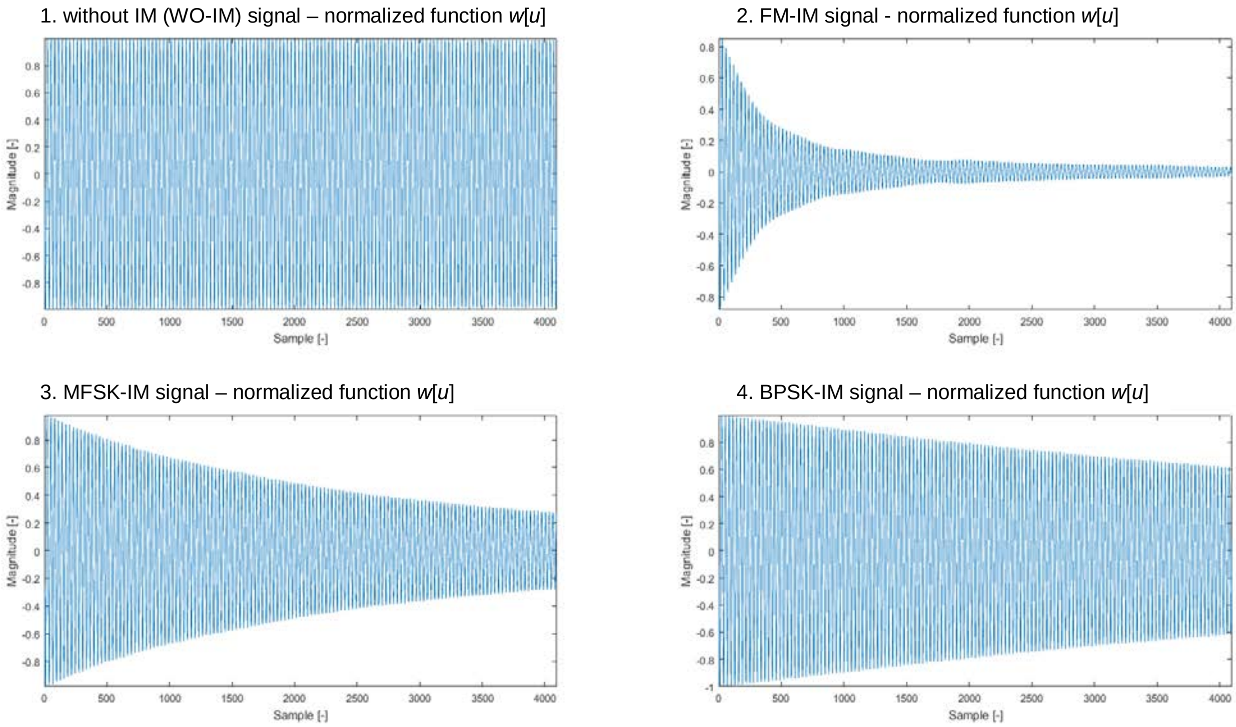

Figure 4: Normalized function *w[u]* examples for every single group of ELINT signals.

From the waveforms of the normalized functions w[u], it is clear that for each of the four defined signal types there is a specific pattern. Automatic classification of the ELINT object is performed by following differences in this patterns.

5.0 MODELING AND SIMULATION RESULTS

To verify the ELINT objects classification process using neural network with proposed data pre-processing, the model programmed in the Matlab program environment was used. Structural schema of model used for ELINT objects classification is shown in Figure 5.

In the simulations performed, the following parameters of the above model were used:

- range of generated pulses carrier frequency f_N values: f_N = (125÷375) MHz;
- range of pulse width values: PW = (8÷128) μs;
- range of frequency deviation values: Δf_N = (1÷10) MHz (just for FM-IM signals);
- frequency modulations for FM-IM signals: increasing linear FM, decreasing linear FM, increasing quadratic FM, increasing logarithmic FM, convex quadratic FM, concave quadratic FM;
- number of subpulses for MFSK-IM signals: 3, 5, or 7;
- used intra-pulse modulations of BPSK-IM signals: Walsh–Hadamard 16 (14^{th} or 6^{th} row in Walsh–Hadamard 16 codes matrix), Walsh–Hadamard 32 (30^{th} or 22^{nd} row in Walsh–Hadamard 32 codes matrix), regular Barker 13, inverse Barker 13; the rows in Walsh–Hadamard 16 and Walsh–Hadamard 32 matrices were selected based on the findings in [15];
- sampling time: $T_S = 1/(30*f_N)$;
- signal to noise ratio *(SNR)* for training dataset … 20 dB;
- number of vectors in training dataset … 512 for every mentioned group of ELINT signals (4 groups), i.e. 2048 overall;
- number of classified vectors (signals) … 1024 for every mentioned group, i.e. 4096 overall;
- computer used for simulations: CPU AMD Athlon II X2 255, RAM 4096 MB DDR3, GPU Radeon HD 4250, operating system Windows 10 64-bit, Matlab 2016a program environment.

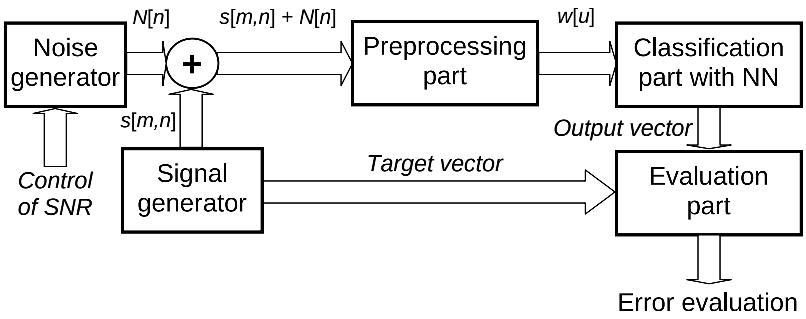

Figure 5: Structural schema of used ELINT objects classification model.

Verification of the correct operation of the automatic ELINT objects classifier was performed in several stages. Several simulations and tests were carried out, which resulted in the following facts:

a) In the first stage of simulations, different types of neural networks were tested. The neural network type "Pattern Recognition Network" was evaluated as the most suitable for the automatic ELINT objects classification with the designed pre-processing. Schematic structure of used neural network- Pattern Recognition Network is shown in Figure 6.

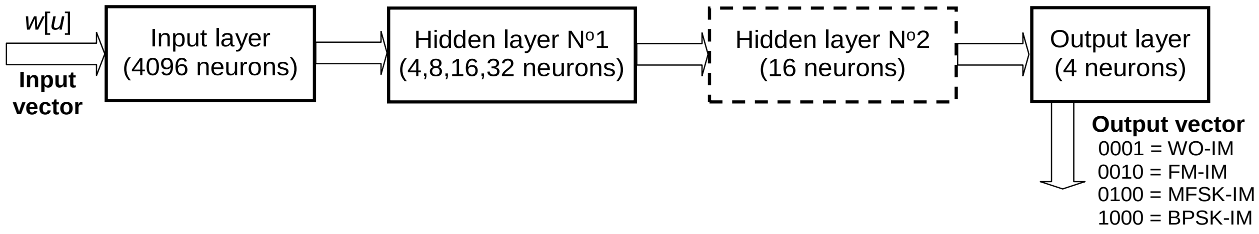

Figure 6: Schematic structure of used neural network - Pattern Recognition Network.

b) In the second stage of the simulations, the problem of optimization of the robustness of this type of neural network was resolved with respect to the number of hidden neurons (4, 8, 16 or 32) and the number of hidden layers (1 or 2). The following parameters were evaluated in the neural network robustness optimization process:

i. Number of correct classified inputs vs. signal to noise ratio *(SNR)* in decibels for tested neural network;

ii. Neural network performance values vs. *SNR*;

iii. Neural network regression values vs. *SNR*;

iv. Mean time for classification of single pulse (include preprocessing algorithm) T_C. Mean time was evaluated only for two Pattern Recognition Network structures (with the best results).

The results of the robustness optimization of Pattern Recognition Network is shown in Table 1-1, Table 1-2, Table 1-3 and Table 1-4.

Table 1-1: Number of correct classified inputs vs. *SNR*

NN - Correct classified inputs		SNR [dB]						
		-8	-6	-4	-2	0	2	4
Neural network	patternnet 4	0,809	0,947	0,973	0,985	0,983	0,985	0,987
	patternnet 8	0,891	0,966	0,977	0,986	0,983	0,986	0,986
	patternnet 16	0,86	0,963	0,977	0,984	0,982	0,984	0,986
	patternnet 32	0,802	0,948	0,974	0,986	0,983	0,984	0,987
	patternnet 16 16	0,797	0,944	0,975	0,985	0,983	0,984	0,987
	patternnet 32 16	0,77	0,931	0,97	0,983	0,981	0,982	0,985

Table 1-2: Neural network performance values vs. *SNR*

NN – Performance values		SNR [dB]						
		-8	-6	-4	-2	0	2	4
Neural network	patternnet 4	0,1271	0,0442	0,025	0,0181	0,0179	0,0159	0,0158
	patternnet 8	0,0664	0,0278	0,0181	0,0145	0,0153	0,0138	0,0134
	patternnet 16	0,0786	0,028	0,0164	0,0126	0,0132	0,0116	0,0114
	patternnet 32	0,1328	0,0388	0,0173	0,0109	0,0119	0,01	0,0096
	patternnet 16 16	0,119	0,0407	0,0204	0,0142	0,0149	0,0133	0,0128
	patternnet 32 16	0,1591	0,0525	0,0235	0,0162	0,0165	0,0149	0,0145

Table 1-3: Neural network regression values vs. *SNR*

NN – Regression values		SNR [dB]						
		-8	-6	-4	-2	0	2	4
Neural network	patternnet 4	0,79504	0,93954	0,97166	0,98276	0,98166	0,98439	0,98488
	patternnet 8	0,88669	0,96279	0,97929	0,98549	0,98322	0,98561	0,98654
	patternnet 16	0,86109	0,95898	0,97819	0,9848	0,98248	0,98533	0,98601
	patternnet 32	0,79332	0,94191	0,97549	0,98555	0,98331	0,98587	0,98697
	patternnet 16 16	0,79169	0,93979	0,97483	0,98509	0,98295	0,98546	0,98667
	patternnet 32 16	0,74794	0,9201	0,97035	0,98286	0,98125	0,98388	0,9848

Table 1-4: Mean time for classification of single pulse (include preprocessing algorithm)

T_c - Mean time [ms]		WO-IM	FM-IM	MFSK-IM	BPSK-IM	Mean value
Neural network	patternnet 8	13,6	14,5	14,1	13,8	14
	patternnet 16	15,2	15,6	15,9	16,1	15,7

Based on the evaluation of the above mentioned parameters, it can be stated that the best results in this approach for ELINT objects classification were achieved by a neural network with one hidden layer containing 16 resp. 8 neurons.

c) In the final phase of the simulations, it was tested how likely it is to classify the above defined signals of ELINT objects using the Pattern Recognition Network structures with the best results. The best results were reached using the Pattern Recognition Networks with one hidden layer containing 16 (NN Nº 1), respectively 8 neurons (NN Nº 2). For each signal class, a set of M = 1024 signals with random variables at the given SNRs was generated. Probability of correct classification p_C is given by the equation

$$p_C = \frac{M_C}{M}, \qquad (10)$$

where M_C is the number of correctly classified signals from a given class.

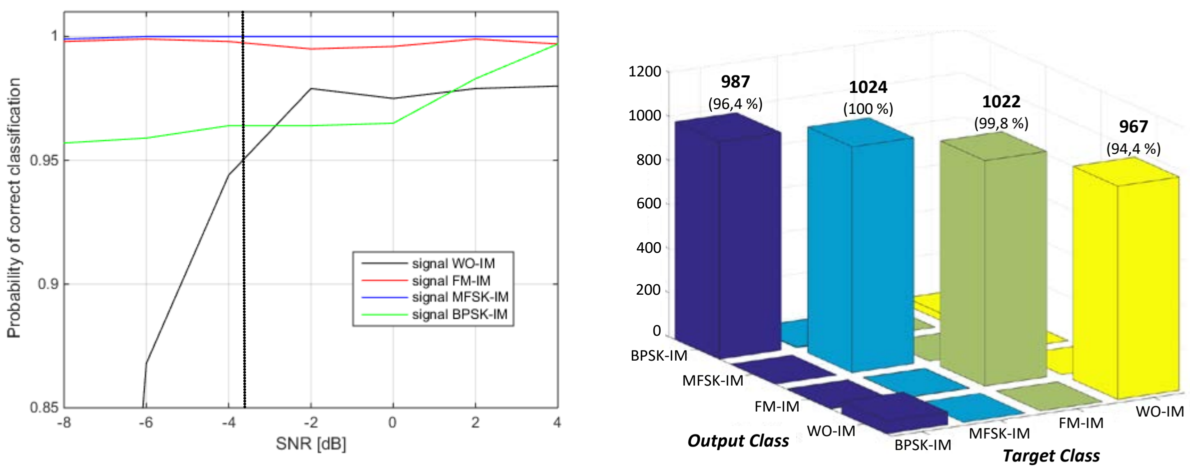

Figure 7: Probability vs. *SNR* (left) and number of correct classified inputs by neural network Nº 1 for *SNR* = -3,75 dB (right).

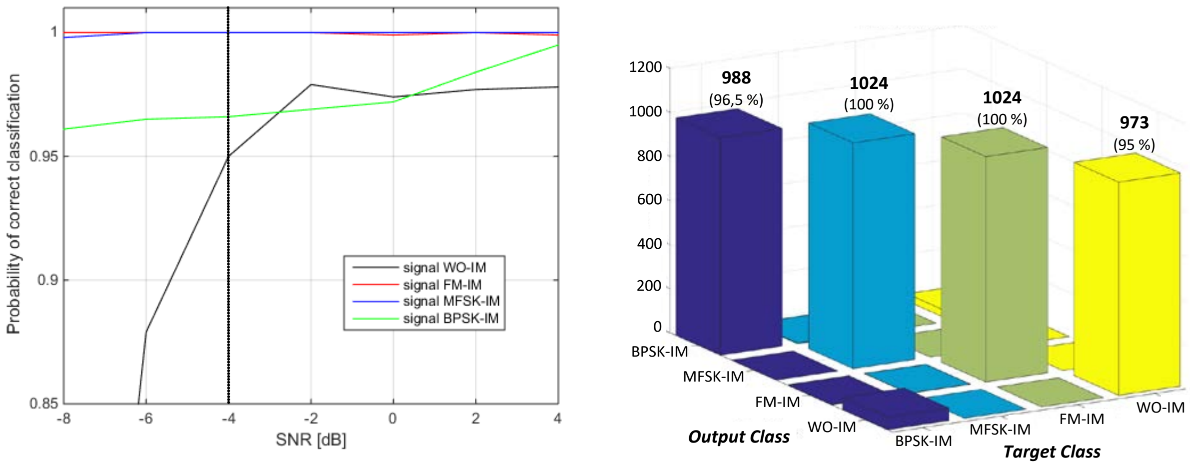

Figure 8: Probability vs. *SNR* (left) and number of correct classified inputs by neural network Nº 2 for *SNR* = -4 dB (right).

The results obtained in the ELINT objects classification by the neural network with one hidden layer containing 16 neurons (NN Nº 1) is shown in Figure 7 and containing 8 neurons (NN Nº 2) is shown in Figure 8.

It is clear from the above figure that neural network Nº 1 very reliably classifies ELINT objects with intra-pulse modulation (p_C > 0,95 also for *SNR* = -8 dB). For ELINT object signals without intra-pulse modulation, this condition applies to SNR = -3,75 dB.

Neural network Nº 2 is working a bit more reliable. It also classifies all of the ELINT objects with intra-pulse modulation with p_C > 0,95 for *SNR* = -8 dB. For ELINT object signals without intra-pulse modulation, this condition applies to SNR = -4 dB. The results obtained with the classification of ELINT objects with the best tested neural networks (patternnet 16 and patternnet 8) are absolutely sufficient for their practical use.

6.0 CONCLUSIONS

A novel method of the ELINT object signals identification approach based on intra-pulse modulation classification is presented in this paper. The algorithm for classification is based on the pre-processing stage and classification stage with neural network (NN) using. The number of correct classified inputs vs. signal to noise ratio for tested NN was recognized and other NN parameters was evaluated. Mean time for classification of single pulse was evaluated for two Pattern Recognition Network structures. Probability of correct classification above 0,95 was reached up to *SNR* = -4dB. Those results are absolutely sufficient for their practical use.

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