Usage of production-based expert system and neural network for signal recognition

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Abstract. At the current paper the system of signal type automatic recognition for the problem of automated testing of radar stations based on collaborative usage of production system and neural network set is presented. The main approaches for solving the problem of automated recognition digital and analog modulation types are shortly outlined. Characteristics calculated based on time-domain and frequency-domain signal representation, typical for the radar impulses are considered. The structural schema of the software for automated classification of radar impulses is presented.

1. Introduction
The problem of automatic modulation classification of radio signals is relevant in many tasks of surveillance and electronic warfare. For example, in case of radio-technical reconnaissance of emissions from airborne radar systems, it is necessary to solve the problem of recognizing and classifying the types of radiating radar stations and their operating modes.

Moreover, automatic recognition systems for types of modulation are needed to automate testing of radar stations.

In the civil applications, automatic modulation classification is widely used for constructing adaptive data transmission channels (so called link adaptation) [1-2]. The principle of operation of devices with an adaptive data transmission channel is based on the fact that in the transmitting device, the modulation unit uses not only one type of modulation, but selects the type of modulation from a predetermined set of types of modulation. The choice of the modulation type depends on the state of the data transmission channel. For noisy data transmission channels, more robust modulations (such as binary phase-shift keying modulation) are used. In clear data transmission channels, more efficient modulations are often used to provide greater data throughput (such as quadrature amplitude modulations).

In this way, the type of modulation used by the transmitter may be changed over time depending on the state of the data transmission channel. Receiving device should automatically determine the type of currently used modulation and change it to correctly receive data [1].

2. Overview of existing approaches in the field of automatic modulation classification
Existing modulation classification algorithms can be divided into 2 main classes:

   1) Probabilistic based algorithms (likelihood-based algorithms);
   2) Feature-based algorithms.
For algorithms based on the probabilistic approach, the model of the received signal and the model of data transmission channel must be known [1]. Then, based on the model of recognized signals, likelihood functions are designed for each type of modulation. After that, based on the intercepted signal samples, the value of the likelihood function is evaluated for each modulation hypotheses.

The decision to classify the signal is made in favor of the candidate with the maximum likelihood function. In practice, due to the high computational complexity of likelihood-based algorithms, it is often necessary to use suboptimal methods based on the feature analysis.

The common approach of feature-based modulation classifier consists of two steps:
1) Selection of informative features for signal classification.
2) Classification of the received signal based on the values of the selected features.

A lot of features are based on analysis of the time samples of the signal or on the spectral representation of the signal [3-6]. For example, in [1] the following features are used to classify digital and analog modulations:

1) The maximum value of the spectral power density of the normalized and centered instantaneous amplitude of the received signal

$$\gamma_{\text{max}} = \max \left| DFT(A_n) \right|^2 / N$$

where DFT() is the discrete Fourier transform, $A_n$ is the normalized and centered instantaneous amplitude of the received signal, and $N$ is the total number of signal samples.

2) Standard deviation of the absolute value of the non-linear component of the instantaneous phase

$$\sigma_{ap} = \left[ \frac{1}{N_c} \left( \sum_{A_n[n] > A} \phi_{NL}[n] - \left( \frac{1}{N_c} \sum_{A_n[n] > A} \phi_{NL}[n] \right)^2 \right) \right]^{1/2}$$

where $\phi_{NL}[n]$ denotes the non-linear component of the instantaneous phase of the n-th signal sample and $N_c$ is the number of samples that meet the condition: $A_n[n] > A$. The variable $A$ is a threshold value which filters out the low-amplitude signal samples.

3) Standard deviation of the non-linear component of the direct instantaneous phase

$$\sigma_{dp} = \left[ \frac{1}{N_c} \left( \sum_{A_n[n] > A} \phi_{NL}[n] - \left( \frac{1}{N_c} \sum_{A_n[n] > A} \phi_{NL}[n] \right)^2 \right) \right]^{1/2}$$

where all parameters remain the same as in the expression for equation 2.

4) Standard deviation of the absolute value of the normalized and centered instantaneous amplitude of the signal samples

$$\sigma_{aA} = \left[ \frac{1}{N} \left( \sum_{n=1}^{N} A_{n}[n] - \left( \frac{1}{N} \sum_{n=1}^{N} A_{n}[n] \right)^2 \right) \right]^{1/2}$$

5) Standard deviation of the absolute value of the normalized and centered instantaneous frequency

$$\sigma_{af} = \left[ \frac{1}{N_c} \left( \sum_{A_n[n] > A} f_N[n] - \left( \frac{1}{N_c} \sum_{A_n[n] > A} f_N[n] \right)^2 \right) \right]^{1/2}$$
Also, wavelet transform based features [2, 7] and high-order statistics based features (high-order moment-based features and high-order cumulant-based features) are widely used [1, 8-9].

After evaluation of the features values the classification of the signal using rules or decision trees is performed.

In addition, machine learning methods can be used instead of manual designing of classification rules. For example, usage of different types of artificial neural networks for signal classification is described in [3, 6, 9-12].

It’s necessary to denote that algorithms presented in the literature are designed for stationary signals recognition, which makes them difficult to use in the specific domains.

3. The structural schema of the software for automated signal classification

At the current study one of the possible methods of collaborative usage of expert system that includes production rule-based system and feedforward neural network – for solving the problem of radiolocation signals recognition is presented.

The proposed structure diagram of the signal classification software is shown in Figure 1.

![Figure 1. Structure diagram of the software for signal classification.](image)

The actions that must be performed by the software in order to classify signals within the proposed approach may be summarized as follows:

- Signal pre-processing. At this step, we need to apply algorithms to increase the informativeness of the signal on the basis of a-priori known information about its problem domain. In case of radar signals, at this step it may be necessary to filter, transfer the carrier frequency of the signal, calculate the spectrum of the signal, etc.
- Fact generation. At this step we need to extract features that later will be used for the signal classification. It is assumed that user sets the number of algorithms (selection of specific algorithms depends on the subject area’s specific) which form the facts representing signal features.
4. Analysis of the features of radar signals

For the developing block of recognition characteristic features in the problem of classification of radiolocation signals it’s necessary to consider main types of such signals. All signals can be broken down into continuous and impulse [13-14]. Besides that, signals are differentiated by type of modulation. Here the signals with linear-chirp modulation, phase-code-shift keying (M-sequences or Barker codes are usually used for phase manipulation) or signals without modulation (simple radio pulses) can be outlined. Impulse signals can be either single or grouped into batches. In case of grouping, different parameters of impulse such as pulse relative duration or carrier frequency could change.

As typical features for the radiolocation signals classification can be distinguished [15-16]:
- type of the radar signal (impulse-type or continuous);
- impulses repetition period;
- presence of absence of grouping signals into batches;
- difference character between impulse batches (changes either pulse/pause ratio or carrier frequency);
- type of intrapulse signal modulation.

In case of signal/noise ratio is large enough some of those facts can be obtained using time-based representation of a signal (for example, it’s easy to clarify whether or not the signal is impulse or continuous, evaluate repetition period of impulses or see whether or not it’s grouped into batches).

The formation of facts which describe presence and type of intrapulse modulation performs as a result of interacting process using the set of neural networks with forward propagation, which were trained to recognize different features, extracted by the form of frequency spectrum of signals. The way of forming features of that type will be reviewed later.

5. Usage of production-based expert system for classification

For the ability of recognition, classes of recognized modulation types should be presented as set of production rules in the knowledge base of decision support system. Within the scope of the production model of knowledge representation, the objects knowledge is represented as following rules:

Rule 1:
IF (condition 1) THEN (action 1)

Rule 2:
IF (condition 2 OR condition 3) THEN (action 2)

Rule 3:
IF (condition 4 AND condition 5) THEN (action 3)

...
memory of the system starts the inference engine (algorithm which controls execution of rules in the knowledge base).

The inference engine performs two main functions:

- Reading of the existing facts from the working memory as well as rules from the knowledge base and adding new facts into the working memory;
- Defining the order of the reading and applying the rules. Such procedure comes down to definition of the search direction (usually inference in such knowledge base might be forward chaining (from data to goal search) or backward chaining (from goal for confirmation – to data)) and method of its realization. The work of the inference engine is based on applying rule called “modus ponens” (if A is true and the rule like “IF A THEN B” exists, then B is true). Those rules are activated when there are facts in the working memory, which satisfy the left part: if the assumption is true then the conclusion is also true.

For the development of software for signals classification the software tool for expert systems creation called CLIPS (C Language Integrated Production System) was used. The choice of this software tool is reasoned with large amount of documentation, openness and easiness of integration with C programs.

CLIPS uses the forward chaining inference using Rete algorithm, supports ability to add new rules during the inference process and different strategies for conflicts realization. For describing the rules and facts from the knowledge base is used object-oriented language COOL, integrated with the inference mechanism.

An example of CLIPS rule is shown on figure 2.

```
(defglobal *S_RD_2* = 10.0) ; set the value of pulse/pause ratio
(defglobal *S_RD_2_min* = (* *S_RD_2* 0.95))
(defglobal *S_RD_2_max* = (* *S_RD_2* 1.05))
defrule is_RD_2
  (Impulse True)
  (Wobble False)
  (Modulation type@)
  (?x) ; set the safe range of variation of pulse/pause ratio
  (test (and (> ?x *S_RD_2_min*) (< ?x *S_RD_2_max*)))
  =>
  (printout t "Signal type = RD_2" crlf)
```

Figure 2. CLIPS rule example.

6. Example of signal classification in terms of the proposed approach

As an example, consider how the process of signal recognition with linear chirp modulation can be performed in terms of the proposed approach. The spectrum, typical for the linear chirp modulation signal is presented on figure 3.
A set of neural networks (figure 5) was trained to recognize in the number of samples of spectrum the specific features (name them as A, B, C, D, E), presented at figure 4.

As a classifier, the fully connected neural network with 7 inputs, 10 neurons in the first layer, 5 neurons in the hidden layer and 1 neuron in the output layer was used.

As an activation function the logistic function (6) was used.

$$\sigma(x) = \frac{1}{1 + \exp(-tx)}$$  \hspace{1cm} (6)

The principle of usage of the set of neural networks is presented on figure 5.
For the training set creation, the samples of the recognized signals with additive white noise were generated. The resulting signal is transformed in its frequency representation with fast Fourier transform algorithm. For the reduction the input data dimension the signal bandwidth is divided into equal segments and inside of each segment the local maximum of the signal spectrum is founded.

On the obtained set of spectral samples were manually distinguished sections, typical for the recognized features, that at the end formed training set for the neural network classifiers. Then, the backpropagation algorithm was used for training.

Example of the feature D recognition is presented on figure 6.

**Figure 5.** Usage of neural networks for feature extraction.

**Figure 6.** Example of the feature D recognition on signal spectrum.
Usage of one neuron in the neural net’s output layer allows to interpret its output value as probability of presence of the spectrum of the recognized feature in the analyzed neighborhood. While setting some probability threshold it’s possible to go to the representation, which describes presence of the recognized feature in the signal spectrum (for example, for probability value > 0.8 we consider that feature exists).

Figure 7 shows application of this approach. Values equal to 1 correspond to presence of the corresponding feature.

![Figure 7. Presence of the recognized feature in the signal spectrum.](image)

Now, based on such representation, to prove the hypothesis of belonging signal to class of signals with linear chirp modulation, the expert system can use following rules:
1) Feature A exists.
2) Feature D exists on the right side of found feature A.
3) In the interval between A and D there are no other features found, except E.

7. Conclusion
Such example shows that process of recognition can be organized in a way that on each of the steps it is not necessary to process entire frequency representation of the signal and search for all features. The analyzed frequency band and set of existing classifiers depend on current state of the working memory in the expert system. Moreover, in case of rebuttal of the current hypothesis, rules which are relevant for other hypotheses should not be calculated from scratch.

References
[1] Zhu Z, and Nandi A K 2015 Automatic modulation classification: principles, algorithms and applications (UK: John Wiley & Sons)
[2] Makarov K S 2014 Methods of modulation recognition Digital Signal Processing 1 29–35
[3] Guldemir H and Sengur A 2007 Online modulation recognition of analog communication signals using neural network Expert Systems with Applications 33 206–214
[4] Sun T, Jia J and Yu G 2016 Automatic modulation recognition of both digital and analog
communication signals *International Conference on Electrical, Mechanical and Industrial Engineering (ICEMIE 2016)* 154–156

[5] Valipour M H, Homayounpour M M and Mehralian M A 2012 Automatic digital modulation recognition in presence of noise using SVM and PSO *6th International Symposium on Telecommunications (IST2012)* 378–382

[6] Le B, Rondeau T W, Maldonado D and Bostian C W 2005 Modulation identification using neural network for cognitive radios *SDR Forum Technical Conference (Anaheim, CA)*

[7] Park C, Choi J, Nah S, Jang W and Kim D Y 2008 Automatic modulation recognition of digital signals using wavelet features and SVM *10th International Conference: Advanced Communication Technology (ICACT 2008)* 387–390

[8] Adjemov S S, Klenov N V, Tereshonok M V and Chirov D S 2015 Methods for the automatic recognition of digital modulation of signals in cognitive radio systems *Moscow University Physics Bulletin* 6 19–27

[9] Adjemov S S, Tereshonok M V and Chirov D S 2015 Type recognition of the digital modulation of radio signals using neural networks *Moscow University Physics Bulletin* 1 23–28

[10] O’Shea T J, Corgan J and Clancy T C 2016 Convolutional Radio Modulation Recognition Networks (ArXiv eprints)

[11] West N E and O’Shea T J 2017 Deep Architectures for Modulation Recognition (ArXiv eprints)

[12] Liu X, Yang D and Gamal A E 2018 Deep Neural Network Architectures for Modulation Classification (ArXiv eprints)

[13] Berdyshev V P, Garin Ye N, Fomin A N et al 2011 *Radar Systems, ed Berdyshev V P* (Krasnoyarsk: Siberian Federal University)

[14] Kanashchenkov A I, Merkulov V I, Gerasimov A A et al 2006 *Radiolokatsionnyye sistemy mnogofunktional’nykh samoletov. T.1. RLS – informatsionnaya osnova boevykh deistviy mnogofunktional’nykh samoletov. Sistemy i algoritmy pervichnoy obrabotki radiolokatsionnykh signalov*, ed Kanashchenkov A I and Merkulov V I (Moscow: Publishing house Radiotekhnika)

[15] Barabanov V F, Grebennikova N I and Donskih D N 2015 Development of the software for classification signals with use of the productional knowledge base *Bulletin of the Voronezh State Technical University* 11(3) 45–48

[16] Donskih D N Barabanov V F 2019 *Proceeding of the International Conference "Applied Mathematics, Computational Science and Mechanics: Current Problems"* (Voronezh, VSU) 224-228