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RESEARCH ARTICLE

Multi-task neural network for solving the problem of recognizing the type of QAM and PSK modulation under parametric a priori uncertainty

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Abstract
Objectives. Automatic modulation recognition of unknown signals is an important task for various fields of technology such as radio control, radio monitoring, and identification of interference and sources of radio emission. The paper aims to develop a method for recognizing the types of signal modulation under conditions of parametric a priori uncertainty, including the uncertainty of carrier frequency- and initial signal phase values. An additional task consists in estimating the offset values of the carrier frequency or signal phase at the initial stage of the recognition process.
Methods. A multi-task learning with artificial neural network and the theory of cumulants of random variables are used.
Results. For signals with a carrier frequency and initial phase shift, cumulant approaches for QAM-8, APSK-16, QAM-64, and PSK-8 modulations are calculated. A multi-task learning with artificial neural network using cumulant features and a data standardization algorithm is presented. The results of the experiment show that using multi-task learning with an artificial neural network provides high accuracy of recognizing QAM-8 and APSK-16, QAM-64 and PSK-8 modulations with small mismatches of the carrier frequency or initial phase. The accuracy of determining the offset values from the carrier frequency or the initial phase for QAM-8, APSK-16, QAM-64, and PSK-8 modulation is high.
Conclusions. The multi-task learning with neural network using high-order signal cumulants makes it possible not only to recognize modulation types with high accuracy under conditions of a priori uncertainty of signal parameters, but also to determine the offset values of carrier frequency or initial signal phase from expected values.

Keywords: recognition, neural network, carrier frequency, initial phase, cumulant feature

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НАУЧНАЯ СТАТЬЯ

Многозадачная нейронная сеть в задаче распознавания вида QAM- и PSK-модуляции в условиях параметрической априорной неопределенности

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Резюме
Цели. Автоматическое распознавание видов модуляции неизвестных сигналов является важной задачей для различных областей техники: радиоконтроля и радиомониторинга, идентификации помех и источников радиоизлучения. Основная цель работы – разработка метода распознавания видов модуляции сигналов в условиях параметрической априорной неопределенности, в т.ч. неопределенности значений несущей частоты и начальной фазы сигнала. Дополнительной задачей является оценка значений отстроек от несущей частоты или фазы сигнала на начальном этапе процесса распознавания.
Методы. Использована многозадачная искусственная нейронная сеть, теория кумулянтов случайных величин.
Результаты. Для сигналов со сдвигом несущей частоты и начальной фазы вычислены кумулянты для модуляции QAM-8, APSK-16, QAM-64 и PSK-8. Представлена использующая кумулянтные признаки и алгоритм стандартизации данных многозадачная нейронная сеть. Результаты эксперимента показали, что использование многозадачной нейронной сети обеспечивает высокую точность распознавания модуляции QAM-8 и APSK-16, QAM-64 и PSK-8 в случае небольших отстроек несущей частоты или начальной фазы. Точность определения значений отстройки несущей частоты или начальной фазы сигнала для модуляции QAM-8, APSK-16, QAM-64 и PSK-8 оказывается высокой.
Выводы. Многозадачная нейронная сеть, использующая кумулянты сигналов высокого порядка, позволяет не только распознавать с высокой точностью виды модуляции в условиях априорной неопределенности параметров сигналов, но определять при этом значения отстроек несущей частоты или начальной фазы сигнала от ожидаемых значений.

Ключевые слова: распознавание, нейронная сеть, несущая частота, начальная фаза, кумулянтный признак

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INTRODUCTION

One of the promising development areas of modern telecommunication systems involves the introduction of intelligent technologies offering the possibility to recognize and analyze the information transmitted through the communication channel. Such intelligent systems can be used to process data in real time, make predictions, and take decisions based on the obtained results. Here, an associated problem consists in recognizing the various types of digital modulation used in data transmission [1–8]. Knowledge of the parameters of received signals informs identification of the transmitting device and restoration of the transmitted information, as well as making it possible to introduce interference into location and communication radio channels. However, parametric uncertainties that can significantly affect the accuracy of recognition often occur under real conditions of information transmission.

At present, the most effective method of automatic recognition of signal modulation types involves the use of multi-task neural networks. The algorithm for recognizing modulation types using a multi-task neural network under conditions of a priori certainty of values of carrier frequency and initial phase of signals is presented in [1, 4]. In [1], for recognizing ten modulations (GMSK, 8-QAM, 16-QAM, 64-QAM, 16-APSK, 32-APSK, BPSK, QPSK, 8-PSK, and 2-FSK)[1], up to 9th order cumulants are used as information features. The results of computer simulation show that a multi-task neural network using high-order cumulants can not only be used to recognize modulation types but also to determine the value of signal-to-noise ratio (SNR) of the received signal with high accuracy. At SNR = 0 dB, the detection accuracy for GMSK, QAM-8, APSK-16, APSK-32, BPSK, and QPSK modulation is 0.98; however, for QAM-16, QAM-64, PSK-8, and FSK-2 modulation, the detection accuracy is lower. Hereinafter, recognition accuracy refers to the probability of correctly identifying a particular type of modulation signal among all the considered types of modulation. The present work aims to analyze the recognition of four modulation types—QAM-8 and APSK-16, QAM-64, and PSK-8—under conditions of parametric a priori uncertainty, as well as to determine the offset of carrier frequency $\Delta\omega$ and initial phase $\Delta\varphi_0$ of the received signal from the expected values at SNR = 3 dB which, according to simulation results, is sufficient for the recognition of signals with an acceptable accuracy. It is assumed that the received signal is subjected to preprocessing providing the transfer to zero frequency, filtering, and signal sampling from the low-pass filter output[2]. The signal obtained as a result of preprocessing is described by the following expression:

$$r_k(t) = A(t)\{\cos[\Delta\omega t + \varphi(t) + \Delta\varphi_0] + \\ + i\sin[\Delta\omega t + \varphi(t) + \Delta\varphi_0]\} = I_k(t) + iQ_k(t),$$

where $A(t)$ and $\varphi(t)$ are the envelope and phase of the signal; $\Delta\omega$ is the carrier frequency offset; $\Delta\varphi_0$ is the initial phase offset; $I_k(t)$ and $Q_k(t)$ are the in-phase and quadrature components of the signal, respectively.

The resulting complex signal $r_k(t)$ and complex-conjugate signal $\overline{r}_k(t) = I_k(t) - iQ_k(t)$ comprise the initial data for calculating moments and cumulants. Formulas for calculating moments and high-order cumulants are described in detail in [1, 9]. Table 1 presents examples of values of cumulants up to 9th order for QAM-64 and PSK-8 modulation with different offset values of carrier frequency $\Delta\omega$ and initial phase $\Delta\varphi_0$. According to the analysis of the resulting cumulant values, it can be asserted that the information content of a particular cumulant about the type of signal modulation depends significantly on $\Delta\omega$ and $\Delta\varphi_0$ offsets. For example, in the absence of offsets, cumulant $C_{2,0}$, being the first in the table, has the same negative sign for both distinguishable types of QAM-64 and PSK-8 modulation; at $\Delta\omega$ = 900 Hz, the cumulant signs are different; while, at Δφ0 = 0.04 rad, signs of cumulants are positive.

ARTIFICIAL NEURAL NETWORKS

Neural network methods of modulation type recognition are based on selecting certain information features that can help in determining the type of modulation and on constructing a knowledge base based on the analysis of these features. Each neural network of modulation type recognition has its own set of used information features and parameters including the type of data processing and activation function. These differences can affect the efficiency of recognition and the overall accuracy of the system. The process of neural network learning is shown in Fig. 1.

[1] GMSK is a Gaussian minimum shift keying.

8-QAM, 16-QAM, and 64-QAM are quadrature amplitude modulations with 8, 16, or 64 levels.

16-APSK and 32-APSK are amplitude and phase-shift keying with 16 or 32 levels.

BPSK is a binary phase-shift keying.

QPSK is a quaternary phase-shift keying.

8-PSK is an 8-phase-shift keying.

2-FSK is a binary frequency-shift keying.

[2] Caravan O.V. *Distinguishing constellations of signals with quadrature amplitude modulation under parametric a priori uncertainty*. Cand. Sci. Thesis (Phys.-Math.). Voronezh; 2010. 120 p. (in Russ.).

Table 1. Values of cumulants of different orders for QAM-64 and PSK-8 modulation

Cumulant \ Modulation	$\Delta\omega = 0$ and $\Delta\varphi_0 = 0$		$\Delta\omega = 900$ Hz		$\Delta\varphi_0 = 0.04$ rad	
	QAM-64	PSK-8	QAM-64	PSK-8	QAM-64	PSK-8
$C_{2,0}$	−0.00913	−0.0063	0.01209	−0.01225	1.08181	1.12291
$C_{3,0}$	−0.03605	0.04699	−0.04641	0.04051	−0.01704	0.00593
$C_{2,1}$	−0.00800	0.00439	0.01381	0.01362	−0.01714	0.00621
$C_{4,0}$	−0.56435	−0.01765	3.12438	3.20105	−0.36449	−0.27393
$C_{2,2}$	−0.61285	−0.97795	0.92006	0.85290	−0.36504	−0.27938
$C_{5,0}$	−0.20728	0.092786	0.04405	0.05804	−0.20601	0.20011
$C_{3,2}$	−0.00930	−0.00627	−0.05664	0.01384	−0.21641	0.19121
$C_{6,0}$	0.05008	−0.06516	0.97633	1.33265	1.17776	1.29652
$C_{3,3}$	1.62832	3.84222	−0.99868	−0.566	1.14810	1.33444
$C_{7,0}$	−1.56151	−0.47311	−1.01121	0.51321	1.33945	−0.51879
$C_{6,1}$	0.59933	−0.50570	−1.20013	−1.02734	1.40554	−0.47957
$C_{4,3}$	−0.12922	0.01030	−0.33111	−0.76300	3.20184	−1.62158
$C_{8,0}$	−12.8750	−1.42191	−191.842	−201.990	−4.24775	−11.0519
$C_{6,2}$	−11.6686	0.01107	−28.2597	−22.6214	−4.12208	−11.3511
$C_{4,4}$	1356.218	1413.430	1412.013	1359.459	1041.279	1197.02
$C_{9,0}$	−8.11293	4.10262	−28.8307	−15.8577	−37.4355	2.39996
$C_{8,1}$	6.42682	5.20209	27.0642	−7.68852	−244.414	108.016
$C_{6,3}$	−121.649	114.854	534.622	368.480	3453.083	4508.33
$C_{5,4}$	2467.71	2217.473	5219.517	4876.258	6296.198	8169.887

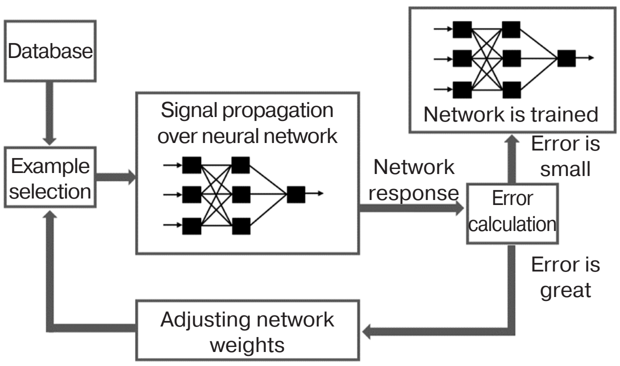

Fig. 1. Process of neural network learning

The neural network itself comprises a system based on many neurons, which receives information, performs simple calculations on it, and then passes it on. After receiving a weighted sum of input signals $net^{(j,1)}$ to its input, each neuron then passes this activation value $\sigma^{(j,1)}$ through the transfer function to obtain the following output values [10–15]:

$$net^{(j,1)} = \mathbf{w}^{(j,1)}\mathbf{x}^{\mathrm{T}} = w_0^{(j,1)} + \sum_{i=1}^{n} w_i^{(j,1)} x_i,$$

$$o^{(j,1)} = f\left(net^{(j,1)}\right),$$

where $\mathbf{w}^{(j,1)} = \left(w_0^{(j,1)}, w_1^{(j,1)}, \ldots, w_n^{(j,1)}\right), j = \overline{1, N_1}$ is the row vector of synaptic connections at the jth neuron input; $\mathbf{x}_i$ is the row vector of the ith input; N_1 is the number of neurons in the first hidden layer.

The activation function $f(net^{(j,1)})$ in a neural network plays an important role in determining the output of each neuron based on its input signal. This function allows the neuron to decide whether to activate and further transmit information or remain inactive. There are many different activation functions that can be used in neural networks, each having its own advantages and limitations. In the paper, the ReLU (Rectified Linear Unit) activation function is used; this comprises a simple non-linear function for transforming the input signal, zeroing out all negative values, and keeping the positive values unchanged. Formally, the ReLU function is defined as follows:

$$o^{(j,1)} = \mathrm{ReLU}(x_i) = \max(0, x_i).$$

Learning this neural network consists in minimizing the error function $E(\overline{w})$ defined by the following expression:

$$E(\overline{w}) = \frac{1}{2}\sum_{l=1}^{N_{\text{out}}}\left(u_l - o_l\right)^2,$$

where u_l and o_l are the desired and actual state of neural network outputs of the lth neuron of the output layer, respectively; N_{out} is the number of neurons in the output layer.

Although there are currently several methods for minimizing the error function [2, 12, and 13], the greatest efficiency of the method is obtained when using the database standardization function. The standardization method (StandardScaler) is one of the data preprocessing methods used in machine learning for reducing all the original values of the dataset to the set of values from distribution with zero mean and standard deviation equal to 1. The standardization process consists of two steps. In the first step, the mean and standard deviation of each feature in the dataset are calculated. At the second step, each feature value is transformed by the following formula [14, 15]:

$$x_i = \frac{z_i - \overline{Z}}{\sigma_z},$$

where z_i is the original data value; $\overline{Z}$ and σ_z is the mean value and standard feature deviation, respectively.

The standardization method results in a standardized scale defining the place of each value in the dataset by measuring its deviation from the mean in standard deviation units to compare the data for use in machine learning. As the example, cumulant values resulted from standardization for QAM-64 and PSK-8 modulation and certain mismatches of frequency and initial signal phase are given in Table 2.

Table 2. Cumulant values resulted from standardization

Cumulant \ Modulation	$\Delta\omega = 0$ and $\Delta\varphi_0 = 0$		$\Delta\omega = 900$ Hz		$\Delta\varphi_0 = 0.04$ rad	
	QAM-64	PSK-8	QAM-64	PSK-8	QAM-64	PSK-8
$C_{2,0}$	−0.04020	−0.03519	0.09287	−0.07583	−0.51078	−0.50800
$C_{3,0}$	0.001785	−0.04103	−0.03306	0.03589	−0.00352	0.000098
$C_{2,1}$	0.02363	0.00961	0.01718	0.01703	−0.00368	−0.000024
$C_{4,0}$	−0.43586	−0.43379	−0.42396	−0.42372	−0.00605	0.00768
$C_{2,2}$	−0.43481	−0.43849	−0.42072	−0.42135	0.00736	0.00891
$C_{5,0}$	−0.00613	−0.00639	−0.00661	−0.00655	0.005990	0.006273
$C_{3,2}$	−0.00892	−0.00816	−0.00861	−0.00798	0.005992	0.006272
$C_{6,0}$	−0.00173	−0.00179	−0.00152	−0.00143	0.03657	0.036584
$C_{3,3}$	0.03518	0.03641	0.03381	0.03404	0.03717	0.03718
$C_{7,0}$	−0.00901	−0.00902	−0.00903	−0.009	−0.00052	−0.000533
$C_{6,1}$	−0.01062	−0.01063	−0.01065	−0.01065	−0.00049	−0.0005
$C_{4,3}$	−0.00693	−0.00696	−0.00698	−0.007	0.00054	0.000528
$C_{8,0}$	0.37488	0.37488	0.37485	0.37485	−0.03074	−0.03074
$C_{6,2}$	0.32239	0.32241	0.32237	0.32238	−0.03235	−0.03236
$C_{4,4}$	−0.38226	−0.38227	−0.38226	−0.38226	−0.34224	−0.34224
$C_{9,0}$	−0.00205	−0.00205	−0.00205	−0.00205	−0.00450	−0.004506
$C_{8,1}$	−0.00829	−0.00829	−0.00828	−0.00829	−0.00401	−0.00401
$C_{6,3}$	−0.02267	−0.02226	−0.02226	−0.02226	−0.33499	−0.33499
$C_{5,4}$	−0.37783	−0.37783	−0.37783	−0.37783	−0.33517	−0.33517

SIMULATION RESULTS

The multi-task neural network simulation is performed in the Python environment using Google Colab notebook [14]. For recognizing two groups of QAM-8 and APSK-16, QAM-64 and PSK-8 modulation, four databases are formed. Of these, the first two databases are formed for recognizing these types of modulation under conditions of carrier frequency offset, each base consisting of 12800 signals (800 signals for each offset value from the carrier frequency). Under conditions of initial phase offset, two databases each consisting of 16000 signals (800 signals for each value of the initial phase offset) are also formed. The simulation results of modulation type recognition under conditions of carrier frequency offset are shown in Figs. 2 and 3. The figures are presented in the form of tables, whose rows and columns correspond to the type of signal modulation and the carrier frequency offset. The cells show the results of modulation type recognition. For example, for Fig. 2, when recognizing QAM-8 signals with a zero-frequency shift (the first line in the figure is QAM-8 0), all 80 signals participating in the computer experiment are recognized correctly. When recognizing QAM-8 signal with a frequency shift of 1800 Hz (QAM-8 1800), 75 signals are recognized correctly, while 5 signals are mistakenly identified as APSK-16 1800.

It is clear from the figures that a multi-task neural network can be used not only to perform the recognition of modulation types, but also to determine the carrier frequency offset values. As described above, the accuracy of recognizing a certain type of modulation is understood as the probability of correct detection of this type of signal modulation among all the considered modulation types. In the simulation, this probability is estimated as a sample average, i.e., the ratio of the number of correctly identified signals with a given type of modulation to the total number of different signal realizations participating in the computer experiment. The recognition accuracy of QAM-8 and APSK-16 modulation with different $\Delta\omega$ values is 0.96. The results of recognition under conditions of initial phase offset are shown in Figs. 4 and 5.

From Figs. 3 and 5, it can be seen that the recognition accuracy of QAM-64 and PSK-8 modulation decreases at a large mismatch of both frequency and phase. This is due to the fact that several cumulant values at a large mismatch have unstable behavior for different signal realizations, while values of these several cumulant themselves differ slightly for these modulation types. However, use of the multi-task neural network provides high accuracy for estimating $\Delta\omega$ and $\Delta\varphi_0$ values.

Experimental results on recognizing the received signal with the unknown $\Delta\omega$ value are shown in Fig. 6. The experiment results in a recognition accuracy of 0.53 for QAM-64 modulation and 0.47 for PSK-8 modulation. The value of the carrier frequency offset $\Delta\omega$ equal to 600 Hz is determined with high confidence.

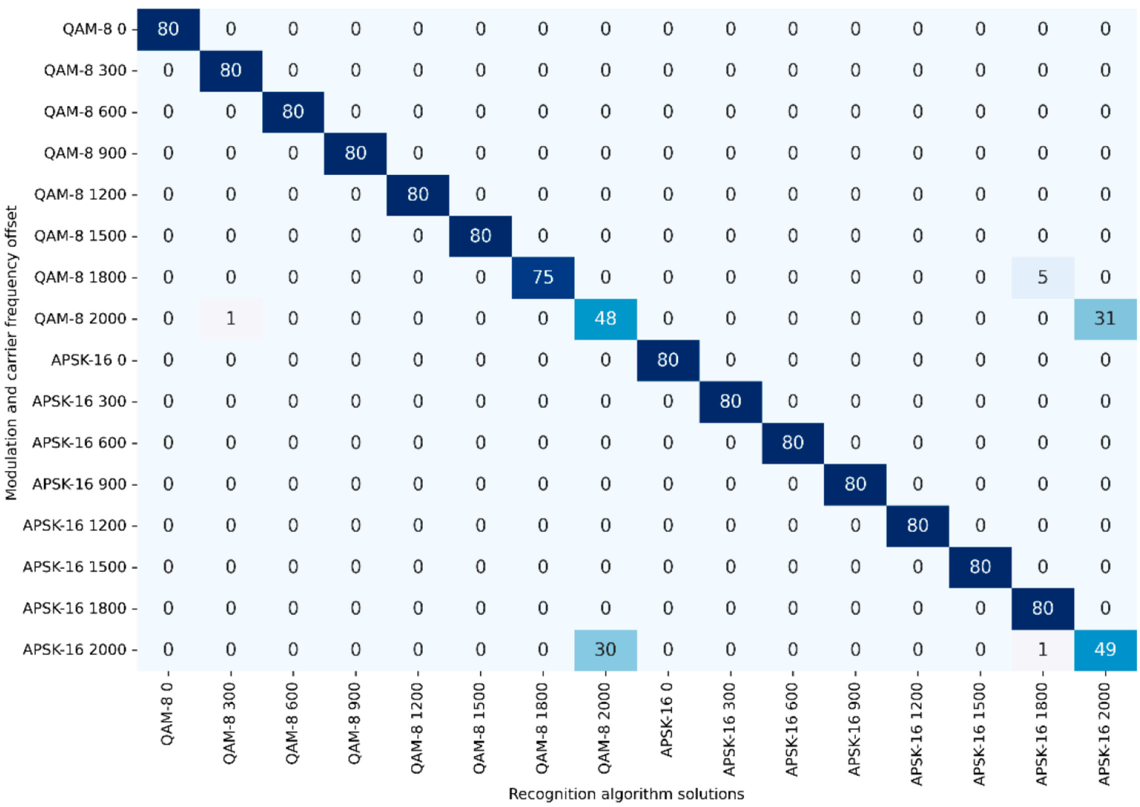

Fig. 2. Recognition results of QAM-8 and APSK-16 modulation at different $\Delta\omega$ values

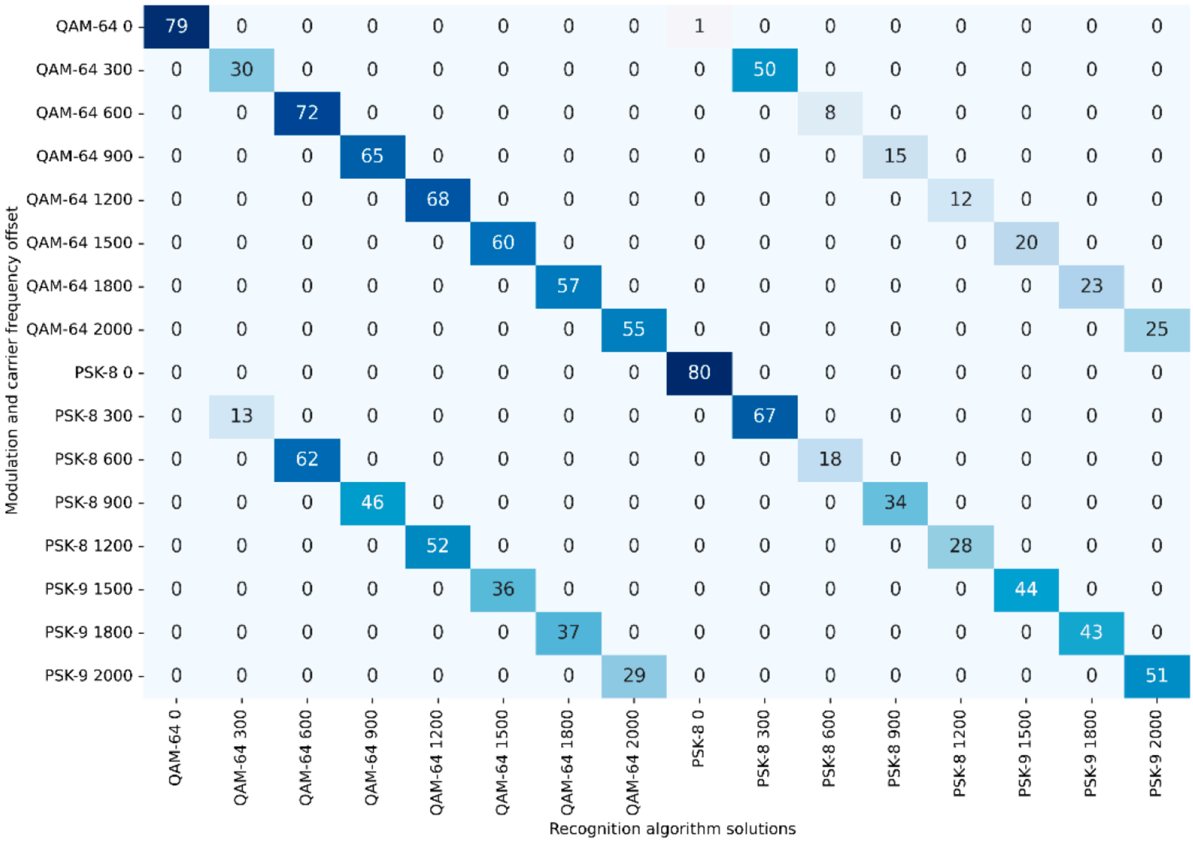

Fig. 3. Recognition results of QAM-64 and PSK-8 modulation at different Δω values

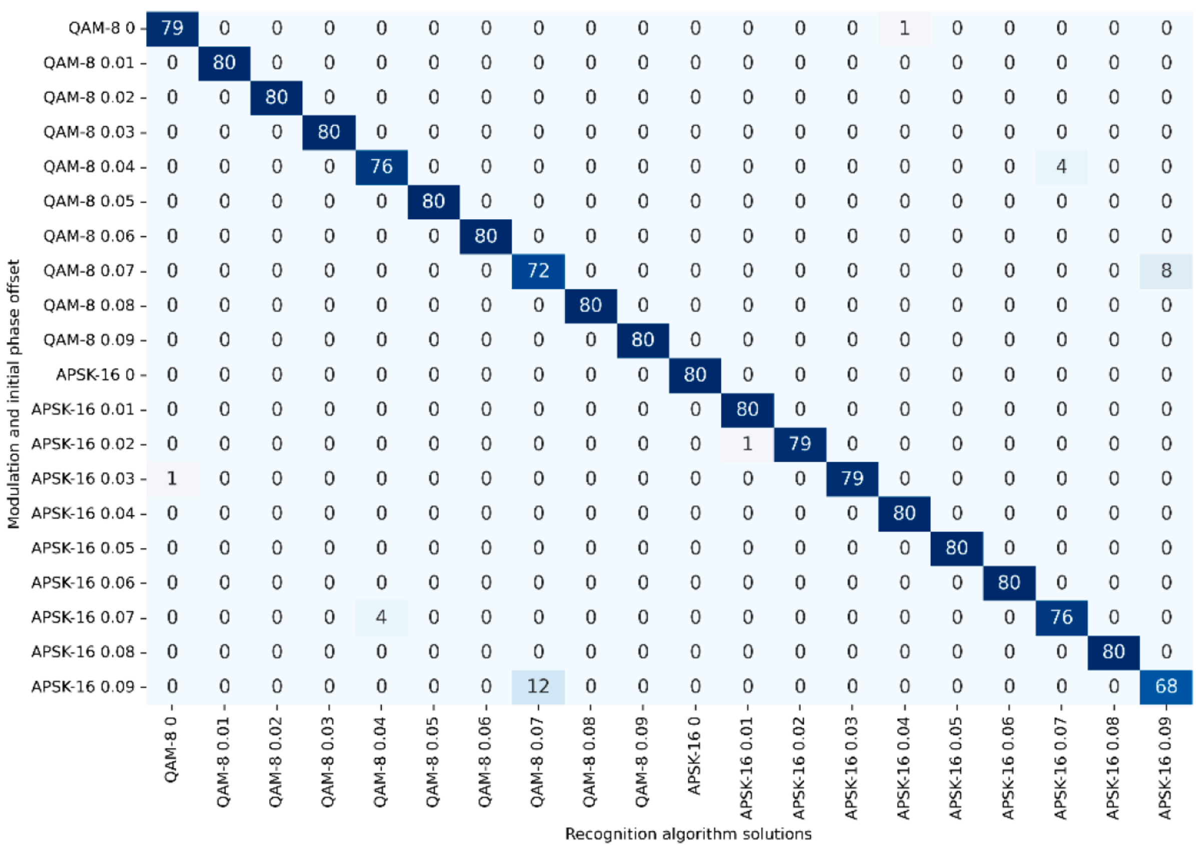

Fig. 4. Recognition results of QAM-8 and APSK-16 modulation at different $\Delta\varphi_0$ values

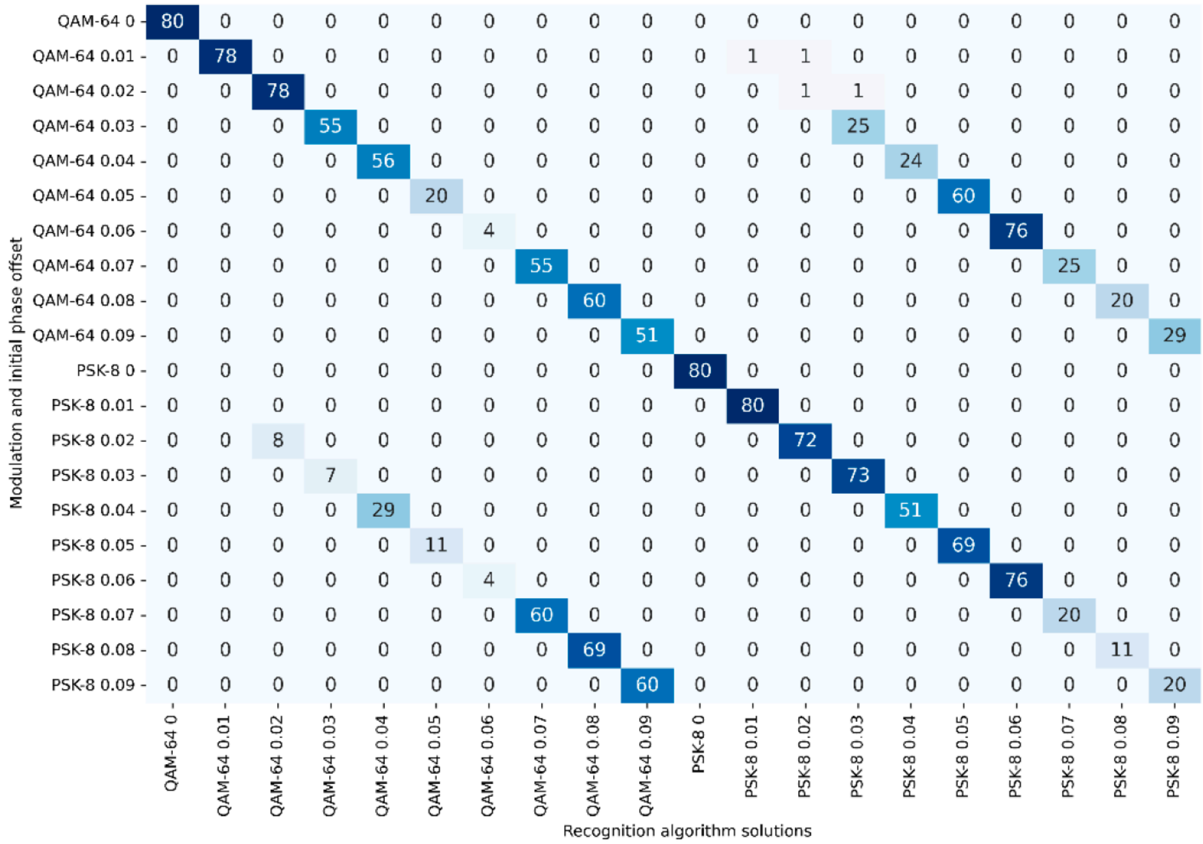

Fig. 5. Recognition results of QAM-64 and PSK-8 modulation at different $\Delta\varphi_0$ values

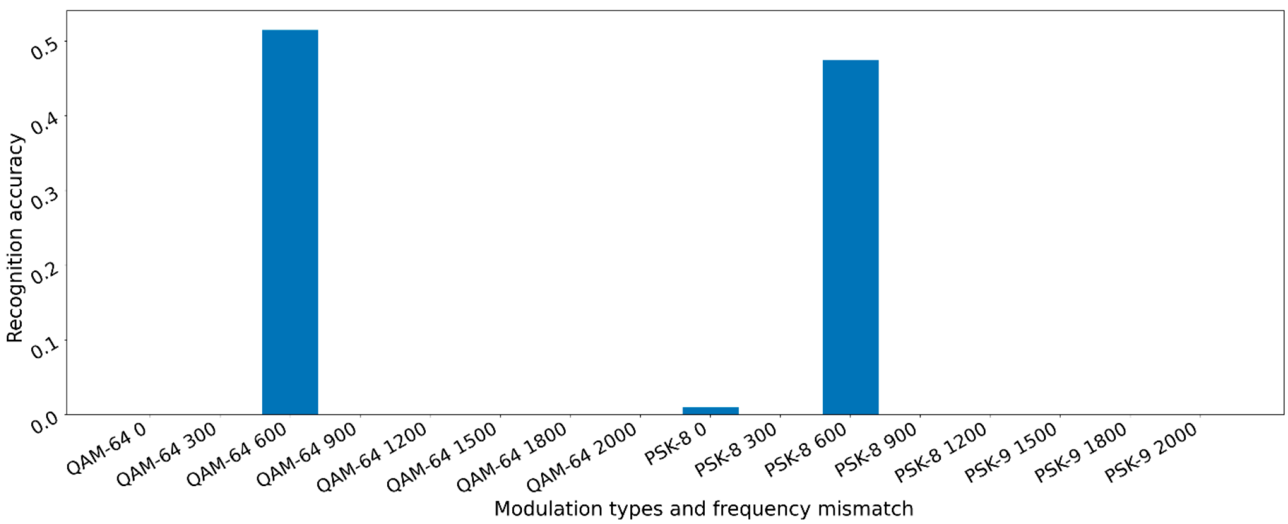

Fig. 6. Experimental result on recognizing the received signal modulation type

CONCLUSIONS

In the paper, the method for recognizing digital modulation types (QAM-8, APSK-8, QAM-64, and PSK-8) in the case of inaccurate knowledge of signal parameters, including carrier frequency and initial phase, is considered. The multi-task neural network is built using the StandardScaler algorithm for data standardization. The simulation results suggest that the multi-task neural network using cumulants as the information feature has the capacity not only to recognize digital modulation types with high confidence in the case of defining the carrier frequency and initial phase values inaccurately, but also to estimate the associated values. In future, it is proposed to consider the recognition of modulation types at simultaneous uncertainty of carrier frequency and initial phase values.

Authors' contribution. All authors equally contributed to the research work.

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