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IMAGE FORMATION IN A MOBILE ROBOT'S OPERATING ENVIRONMENT AND CLASSIFICATION USING NEURAL NETWORKS AND LOGICAL-LINGUISTIC ALGORITHMS

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Abstract

Image Formation in the Environment of a Mobile Robot's Choice and Their Classification Using Neural Networks and Logical-Linguistic Classification Algorithms. The article investigates the task of improving the accuracy and speed of image classification for mobile robot and UAV control systems under conditions of data uncertainty. An integrated approach combining fuzzy logic methods (logical-linguistic classification (LLC)) and neural network technologies is proposed. A mathematical model for image representation using attribute membership functions has been developed, allowing it to work with noisy and incomplete data. An algorithm for generating test data based on etalon images with an adjustable noise level ($0 - 100\%$) was created. A comparative testing of the neural network approach and the LLC algorithm was conducted on sample sizes ranging from 680 to 68 000 images. It was experimentally established that the neural network demonstrates high efficiency with large data volumes and high noise levels ($> 80\%$), while the LLC algorithm is more effective with small samples and moderate noise levels ($50 - 60\%$). The minimum training sample size for stable operation of the neural network was determined to be 6 800 images. The practical significance of the work lies in the development of an adaptive classification system capable of operating in real-world conditions of robotic complexes with variable levels of informational uncertainty.

Key words

Neural networks, fuzzification, logical-linguistic classification, logical-probabilistic classification, classified images.

1 Introduction

Mobile robots represent complex physical and technical objects controlled by intelligent systems. For making correct decisions in mobile robot control [Gorodetskiy et al., 2021], [Ivanko et al., 2020], [Toporin, 2020], including unmanned aerial vehicles (UAVs), the accuracy and speed of image classification in the environment are critically important. These parameters directly impact the failure-free execution of tasks such as target detection, identification, and classification [Dey et al., 2019]. The most complex and significant among these is the task of image detection and classification.

The main task involves making decisions based on the analysis and classification of images received from the robot's measurement systems, including machine vision systems. The development of intelligent classifiers for mobile robot decision-making systems is a key element in synthesizing their control systems. The image recognition task involves analyzing various situations, including dynamic ones, which represents a actual problem from the cyber-physical approach perspective.

Control of such objects is based on information from numerous measurement tools. However, many systems operate under uncertainty caused by measurement errors. Although multiple measurements are usually taken to minimize errors, this opportunity is often unavailable for UAVs, leading to incomplete and contradictory information. In this regard, the goal of data analysis is to build classification models and create decision rules for assigning images to specific classes [Gorodetskiy et al., 2021], [Zhang et al., 2024], [Vagin et al., 2008].

In technical vision systems [Botuz, 2020], [Alpatov et al., 2017], sets of images $G = \{g_1, g_2, \dots, g_n\}$ and etalon images $G = \{g_1, g_2, \dots, g_n\}$ are formed. These sets represent ordered collections of logical variables, with each element characterized by a set of features of various types.

For building decision rules, classical algorithms forming transparent and interpretable models, such as decision trees and production rules (Section 3), are traditionally used. These methods provide understandable decision-making logic, which is particularly important in safety-critical systems, though their effectiveness is limited when working with high-dimensional data and under significant noise conditions.

Currently, artificial neural networks (NN) [Makarenko et al., 2020], [Babich et al., 2025], [Pham Cong Thang et al., 2024], [?] are widely used for solving image classification tasks. These methods demonstrate high effectiveness when processing large volumes of noisy data, providing accurate approximation, classification, and image recognition. The key advantages of neural network approaches include self-learning capability, noise resistance, and adaptability to changing conditions.

However, under conditions of limited source information, which is characteristic of many practical mobile robot control tasks, the effectiveness of neural network methods may decrease. In such cases, the application of logical -linguistic methods [Gorodetskiy et al., 2021] appears promising, as they possess a transparent structure, are easily interpreted by humans, and show high effectiveness when working with small data samples and moderate noise levels.

This research conducts a comparative analysis of the effectiveness of neural network, logical-linguistic, and classical classification algorithms for image recognition tasks in mobile robot and UAV control systems. The aim of the study is to develop an adaptive hybrid classifier that optimally combines the advantages of the considered methods, depending on data volume, noise level, and requirements for result interpretability. The paper presents criteria for selecting the optimal classification method and provides experimental justification for the effective application areas of each method.

Thus, to achieve maximum classification effectiveness, a comprehensive approach integrating the strengths of all methods is proposed. Such synthesis allows compensating for the disadvantages and enhancing the advantages of each individual method.

For systematically solving the identified problems, the next section presents a generalized description of the task of forming classification models, which formalizes the approach to creating hybrid classifiers combining the advantages of neural network and logical-linguistic methods.

2 Generalized Description of the Task of Forming Classification Models

The process of building classification models for mobile robot control can be described as follows.

In the first step, from the set of images G, a subset of images g_{O1} belonging to class o_1 is selected and assigned the name of this class. Then, from the set $O^1 = O \backslash g_{O1}$, a subset of images g_{O2} belonging to another class is selected, after which from the set of remaining images $O^2 = O^1 \backslash g_{O2}$, images g_{O3} belonging to class o_3, are selected and assigned the name of this class. This process continues until all images from the database are exhausted, i.e., $((((O \backslash g_{O1}) \backslash g_{O2}) \dots) \, g_{Ok}) = O^k$. If it happens that all images and etalon images are exhausted but there remain unclassified images, i.e., $O^k \neq \emptyset$, then these images are assigned to a new class $(k+1)$ and temporarily stored in the database under this name. There may be many such images. In this case, the task of partitioning the $(k+1)$ class into new etalon images may be posed, and accordingly, assigning these images to the newly introduced etalons.

Typically, neural networks [Sikorskiy, 2017], [Karasikov et al., 2016] with training of formed samples are used for extracting image classes. To extract the O_q-th class from images, a training sample $K_q = K_q^+ \cup K_q^-$ can be constructed, where $K_q^+ \subset O_q$ and $K_q^- \subset G_q$. Based on the training sample K_q, a rule can be built that maps positive (etalon) and negative (classified) images of the training sample. The decision rule is considered correct if it subsequently successfully recognizes images that were not initially included in the training sample.

The described general approach to forming classification models defines the basic principles of organizing the classification process; however, its practical implementation requires the development of specific algorithms for constructing decision rules. These algorithms must ensure:

-Effective separation of the image set into classes;
-Construction of correct decision rules based on training samples;
-Generalization capability for working with new, previously unseen images.

The next section discusses specific algorithms that implement the described classification scheme and enable the construction of effective decision rules.

3 Algorithms for Forming Decision Rules

A number of algorithms are known that form decision rules in the form of decision trees [Quinlan, 1986] or sets of production rules. These primarily include the UD3 and C4.5 algorithms [Quinlan, 1996], [Clark et al., 1989], the CN2 algorithm [James et al., 2013], and several others.

Research and experimental results have revealed the advantages and disadvantages of these algorithms. Specifically, with noise levels up to 25% across various training samples, classification accuracy for the UD3 algorithm ranged from 78% to 85%, while for the C4.5 algorithm it ranged from 75% to 80%. At higher noise levels, such algorithms become ineffective. To overcome these limitations, the use of so-called structural-linguistic methods and artificial neural networks is proposed.

The structural-linguistic method formed the basis for Logical-Probabilistic Classification (LPC) and Logical-Linguistic Classification (LLC) algorithms, which utilize, for example, feature selection based on a probabilistic cross-entropy approach [Abellan et al., 2017], [Dubnov, 2020]. Etalon [Gorodetskiy et al., 2021] proposes logical-probabilistic algorithms for solving classification problems, where classification is performed by calculating the minimum sum of squared differences between the probability values of the elements of the attribute strings of the etalons and the classified images.

However, in real-world UAV operating conditions, obtaining data about image attributes and determining their probabilities in the selection environment is not always feasible. It is significantly simpler and faster to compute membership function values $\mu(.)$ of attributes through their fuzzification [Zade, 1976], [Zak, 2013]. Therefore, for image classification in the UAV selection environment, it is advisable to use logical-linguistic decision rules based on fuzzy or incomplete information [Nogin, 2019] and corresponding LLC algorithms. With small data volumes, LPC and LLC algorithms can achieve high classification speed with accuracy around 80% and noise levels up to (30–50)%.

If the noise level increases by more than 50% relative to the signal level, a trained neural network can be used. However, one of the main disadvantages of neural networks is the difficulty in preparing training samples due to insufficient available data. Furthermore, real-world UAV operating conditions demonstrate that obtaining data about image attributes is a complex task and is limited in nature. Therefore, neural network training can reach an impasse and take considerable time.

To solve this problem, a comprehensive approach combining logical-linguistic and neural network classification methods is proposed. This maximizes classifier effectiveness by enhancing the positive properties of each method while compensating for their disadvantages.

Logical-linguistic methods possess an open structure, are easily interpreted by humans, and demonstrate high effectiveness when working with small data samples and moderate noise levels. Within the combined approach, these methods are proposed for preliminary data analysis. Based on this analysis, a etalon training sample is formed, and then the logical-linguistic approach generates new examples to create a training sequence that accounts for noise influence, which is used in neural network methods. This allows involving human expert opinion only for verifying data in the etalon sample obtained by logical-linguistic methods.

In the area of neural network methods, the use of a network trained on generated test sequences for image classification in mobile robot machine vision systems is proposed. Simulation of a hybrid classifier based on this comprehensive approach has demonstrated its high effectiveness for solving image classification tasks in mobile robot machine vision systems.

The proposed comprehensive approach requires verification of its effectiveness and performance under conditions as close as possible to real-world scenarios. To address this task, computer modeling was conducted.

4 Computer Modeling

To verify the theoretical principles and conduct a comparative analysis of the effectiveness of the proposed hybrid approach, computer modeling of the image classification process was performed. The modeling included stages of etalon data formation, training sample generation with various noise levels, and algorithm testing.

4.1 Input Data and Etalon Images

A model of etalon images divided into five groups was developed:

s_1 — Environment;
s_2 — Ground vehicles;
s_3 — Watercraft;
s_4 — Aircraft;
s_5 — People.

Each group contained a set of etalon images $O_i(s_i)$. A total of 34 etalons were defined, for example:

Group s_1 used etalons of the following images: $O_1(s_1)$ — Desert; $O_2(s_1)$ — Steppe; $O_3(s_1)$ — Sea; $O_4(s_1)$ — Lake; $O_5(s_1)$ — River; $O_6(s_1)$ — Pond; $O_7(s_1)$ — Mountains; $O_8(s_1)$ — Rocks; $O_9(s_1)$ — Hills; $O_{10}(s_1)$ — Deciduous forest; $O_{11}(s_1)$ — Coniferous forest; $O_{12}(s_1)$ — Mixed forest; $O_{13}(s_1)$ — Tropical forest.

Group s_2 used etalons of the following images: $O_{14}(s_2)$ — Construction/road vehicle; $O_{15}(s_2)$ — Truck; $O_{16}(s_2)$ — Passenger car; $O_{17}(s_2)$ — Bus; $O_{18}(s_2)$ — Specialized equipment; $O_{19}(s_2)$ — Agricultural machinery; $O_{20}(s_2)$ — Motorcycle.

Group s_3 used etalons of the following images: $O_{21}(s_3)$ — Yacht or boat; $O_{22}(s_3)$ — Tugboat; $O_{23}(s_3)$ — Passenger liner; $O_{24}(s_3)$ — Cargo ship; $O_{25}(s_3)$ — Container ship.

Group s_4 used etalons of the following images: $O_{26}(s_4)$ — Passenger plane; $O_{27}(s_4)$ — Helicopter; $O_{28}(s_4)$ — Cargo plane; $O_{29}(s_4)$ — UAV.

Group s_5 used etalons of the following images: $O_{30}(s_5)$ — Young man; $O_{31}(s_5)$ — Young woman; $O_{32}(s_5)$ — Elderly man; $O_{33}(s_5)$ — Elderly woman; $O_{34}(s_5)$ — Child.

A set of 10 attribute types $(Y_1 - Y_{10})$ was used to describe the images, each characterized by seven linguistic values $(y_1 - y_7)$. For example:

Type Y_1 "Contour size": y_{11} — Very small; y_{12} — Very small; y_{13} — Small; y_{14} — Medium; y_{15} — Large; y_{16} — Very large; y_{17} — Super large.

Type Y_2 "Aspect ratio": y_{21} — Length much greater than width; y_{22} — Length greater than width; y_{23} — Length slightly greater than width; y_{24} — Length equal to width; y_{25} — Height (depth) much greater than width; y_{26} — Height (depth) greater than width; y_{27} — Height (depth) equal to width.

Type Y_3 "Surface Irregularity": y_{31} — Smooth; y_{32} — Very minor; y_{33} — Very small; y_{34} — Small; y_{35} — Large; y_{36} — Very large; y_{37} — Very significant.

Type Y_4 "Speed of Movement": y_{41} — Zero; y_{42} — Very slow; y_{43} — Slow; y_{44} — Medium; y_{45} — High; y_{46} — Very high; y_{47} — Extremely high.

Type Y_5 "Surface Color": y_{51} — Gray; y_{52} — Blue; y_{53} — Dark Blue; y_{54} — Green; y_{55} — Lettuce-green; y_{56} — Orange; y_{57} — Yellow.

Type Y_6 "Surface Temperature": y_{61} — Very low; y_{62} — Low; y_{63} — Medium; y_{64} — Slightly warm; y_{65} — Warm; y_{66} — High; y_{67} — Very high.

Type Y_7 "Temperature Non-Uniformity": y_{71} — Uniform; y_{72} — Slightly non-uniform; y_{73} — Moderately non-uniform; y_{74} — Considerably non-uniform; y_{75} — Highly non-uniform; y_{76} — Very highly non-uniform; y_{77} — Significantly non-uniform.

Type Y_8 "Sound Volume": y_{81} — None or undefined; y_{82} — Very quiet; y_{83} — Quiet; y_{84} — Medium; y_{85} — Variable; y_{86} — Loud; y_{87} — Very loud.

Type Y_9 "Sound Pitch": y_{91} — Undefined; y_{92} — Variable; y_{93} — Very high; y_{94} — High; y_{95} — Medium; y_{96} — Low; y_{97} — Very low.

Type Y_{10} "Odor": y_{101} — None or undefined; y_{102} — Slightly coniferous; y_{103} — Coniferous; y_{104} — Slightly floral; y_{105} — Floral; y_{106} — Slightly gasoline-like; y_{107} — Gasoline-like.

4.2 Formation and Simulation of the Image Database

Each etalon image O_i was described by a string of membership function values μ_{iN} for $N = 70$ attributes (10 types $*$ 7 values each). These a priori values were established by experts. The general form of the etalon string: $O_i\,/\mu_{i1}\mu_{i2}\mu_{i3}\ldots\mu_{iN}/$.

The algorithm for generating a new image G_i with noise was as follows:

4.2.1 Formation of the etalon database A database of etalon image strings $O_1(s_1)$ ... $O_{34}(s_5)$ was created, where each membership function value μ_{ik} for the k-th attribute of the i-th image was set by an expert.

$O_{16}(s_2) =$ / 0 0.3 0.7 0 0 0 0 0 1 0 0 0 0 1 0 0 0.3 0.5 0.2 0 0 0 0 0.2 0.2 0.4 0.2 0 0 0.2 0.2 0.1 0.1 0.2 0.2 0 0 0 0.2 0.6 0.2 0 0 0 0 0.4 0.5 0.1 0 0 0 0.3 0.5 0.2 0 0 0 0 0 0.5 0.5 0 0 0 0 0 0 0 0 1 / passenger car.

4.2.2 Etalon Selection A etalon row was selected either randomly or deliberately, for example, the row for the "Passenger car" image $O_{16}(s_2)$.

4.2.3 Setting the Noise Level The parameter r was defined, which sets the maximum error (noise) level — from 0% to 100% of the signal level.

4.2.4 Generation of Noisy Attributes For each of the 70 attributes, a random number R_{in} was generated, uniformly distributed on the interval $[0, 1]$.

The noise value for the given attribute was calculated: $R_{Gin} = R_{in} * r$.

A new value for the membership function of the attribute for the noisy image was calculated, taking into account the significance coefficient q_k: $G_i(\mu_{ik}) = |(O_i(\mu_{ik}) - R_{Gin})| * q_k$.

The significance coefficients q_k (integers from 1 to 10) for different attribute groups were set by experts. For example, for the "Passenger car" the following were set: $q_1 = 3$; $q_2 = 4$; $q_3 = 6$; $q_4 = 7$; $q_5 = 4$; $q_6 = 7$; $q_7 = 6$; $q_8 = 7$; $q_9 = 2$; $q_{10} = 10$.

4.2.5 Saving the New Image The generated row of membership function values for the image G_i was saved to the database.

Using this algorithm, an expanded database containing 68 000 images was generated. This database was used for subsequent machine learning of the neural network and for testing the logical-linguistic classification (LLC) algorithms.

The resulting database serves as the foundation for a comparative study aimed at evaluating the advantages and disadvantages of two fundamentally different classification approaches: an interpretable fuzzy logical-linguistic algorithm and a neural network "black box." Analyzing their performance on

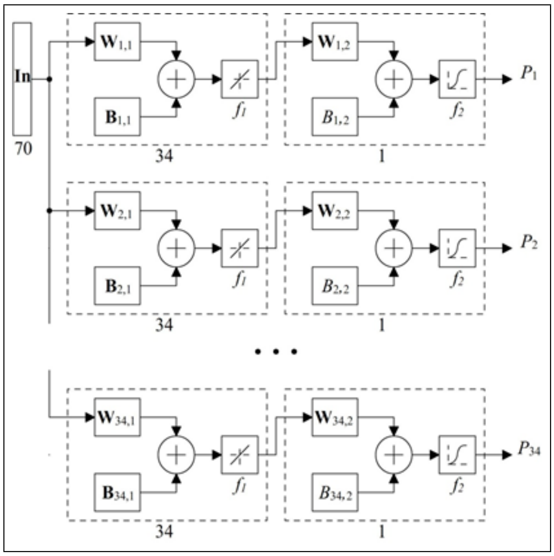

Figure 1: Neural Network Structure

a single test dataset will help identify the optimal application areas for each method in the context of machine vision tasks for a mobile robot.

4.3 Using Neural Networks and LLC Algorithm for Image Classification

The next stage of the research involved the practical application of classification methods to the simulated data. An artificial neural network and the logical-linguistic classification algorithm were selected as the primary tools.

The simplest type of artificial neural network was chosen - a Feedforward Neural Network. This is a classical and well-studied approach, and it is correct for solving classification problems of etalon images based on their vector features.

The neural network consists of 34 parallel channels that learn independently using the error backpropagation algorithm. This neural network is designed to recognize 34 different images. The structure of the neural network is shown in Fig. 1. All etalon images are numbered from 1 to 34, with each channel assigned a number encoding the corresponding image. The input to the neural network is a feature vector In, encoding the image using 70 attributes, which are fed simultaneously to the inputs of all neural network channels.

The channel structure is identical: each consists of two neuron layers. The first layer contains 34 neurons with weights $\mathbf{W}_{i,1}$, biases $\mathbf{B}_{i,1}$ and linear activation functions f_1. The second layer consists of one decision neuron with weights $\mathbf{W}_{i,2}$, bias $\mathbf{B}_{i,1}$ and a sigmoid activation function f_2.

The ideal case of image recognition would be the output P_i of the decision neuron equal to 1 if the image corresponds to the channel number encoding that image, or 0 if the image does not match the channel number. In the presence of noise and images differing from the etalon, the outputs of the channels' decision neurons range from 0 to 1. The channel number with the maximum output value from its decision neuron is then selected, which encodes the recognized image.

A software package in the MATLAB environment was used to implement the neural network as a computer model. The proposed architecture allows for increasing the number of recognizable images by adding new parallel channels. During the modeling and training of the neural network, it was established that the minimum size of the training sample required for stable recognition is 6 800 training images. As the sample size increases, the percentage of incorrect recognitions decreases.

The results of the computer experiment are shown in Fig. 2 for 6 800 images and Fig. 3 for 68 000 images. In Fig. 2, the x-axis represents the noise-to-signal ratio in percent, and the y-axis represents the algorithm accuracy in percent.

For comparison, the created database was tested using LLC algorithms. The testing results are presented in Fig. 4 (680 images), Fig. 5 (6 800 images), and Fig. 6 (68 000 images). The x-axis shows the noise-to-signal ratio in percent, and the y-axis shows the algorithm accuracy in percent.

Based on the results of computer tests of the neural network and the LLC algorithm, integral performance metrics can be calculated:

$$I = \int_{0}^{100} l(x)\,dx,$$

where: $l(x)$) is the accuracy function (see Fig. 2 – Fig. 6), and x is the noise level ($0 \le x \le 100$).

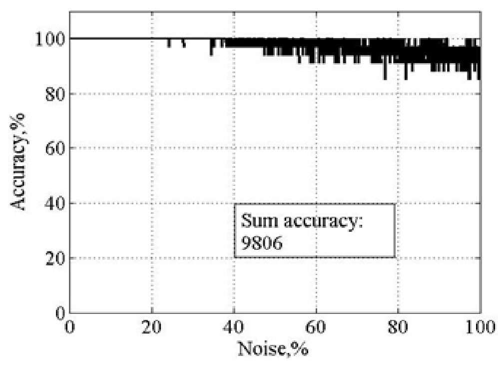

Figure 2: Classification accuracy versus noise level for 6 800 images using a neural network

Table 1 presents the input and output data from the test trials, along with integral performance evaluations. Column 1 presents number of images (input

Table 1: Input and output data of computer testing

1	2	3	4	5	6
680	20	5 – 100	5	5624	–
6 800	200	0.5 – 100	0.5	6069	9806
68 000	2000	0.05 – 100	0.05	6107	9825

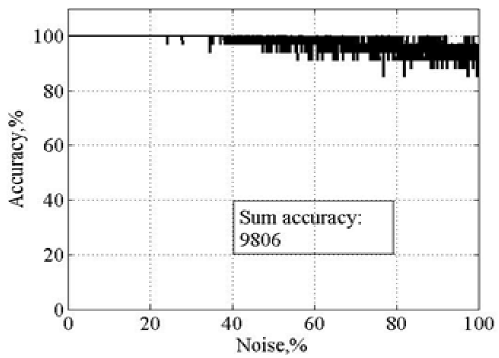

Figure 3: Classification accuracy versus noise level for 68 000 images using a neural network

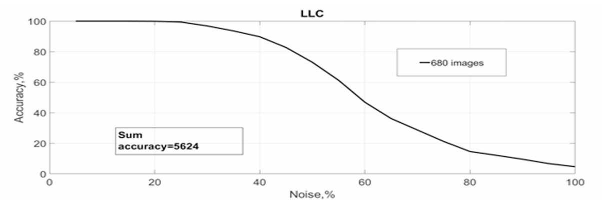

Figure 4: Classification accuracy versus the noise level for 680 images using the LLC algorithm

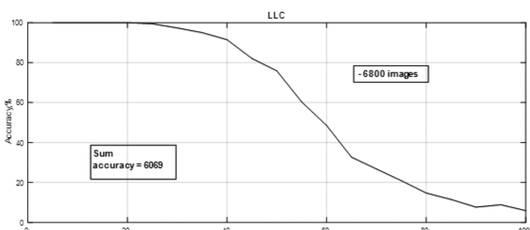

Figure 5: Classification accuracy versus noise level for 6 800 images using the LLC algorithm

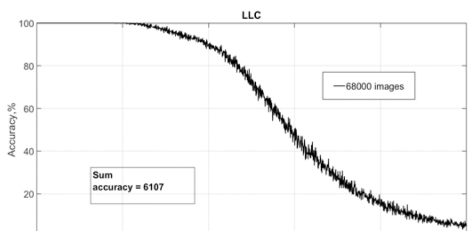

Figure 6: Classification accuracy versus noise level for 68 000 images using the LLC algorithm

data), 2 — number of noise steps, 3 — noise change limits vs signal level, %, 4 — noise steps, %, 5, 6 — integral performance assessment, I (LLC and NN correspondingly).

With a sample size of 680 images, it was not possible to train the neural network, hence the absence of results in Table 1. As can be seen from Table 1, at high noise levels, the obtained mean Integral performance assessment for the neural network trained on samples of 6 800 and 68 000 images are higher than those for the LLC algorithms.

5 Conclusion

The conducted research confirms the effectiveness of a comprehensive approach to the problem of image classification in a mobile robot's operational environment, based on the use of both neural network models and logical-linguistic classification algorithms.

A methodology for forming and computer modeling a database of etalon images with adjustable noise levels has been formulated, enabling a comparative analysis under controlled conditions that closely approximate real-world UAV operation.

The effective application areas for each method have been established:

LLC algorithms demonstrate high effectiveness at noise levels of 50–60% and with small sample sizes. Their key advantages in this scenario are high operational speed, transparency of decision-making (interpretability), and low computational costs.

Neural network algorithms (specifically, the feedforward network) show superiority at noise levels exceeding 80% and with large data samples. Their robustness to strong noise is attributed to their ability to model complex and nonlinear dependencies.

The practical significance of the work lies in the fact that improved classification accuracy and speed directly contribute to enhancing the autonomy and safety of mobile robots (e.g., UAVs). This enables them to function effectively under conditions of uncertainty and make informed decisions in situational control systems, minimizing the risk of accidents.

Thus, the results of the work indicate the promise of hybrid systems where the classifier is selected adaptively, depending on current conditions (noise level, volume of available data, and computational resources). This direction forms the basis for future research.

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