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Articles

Synthesis of a hybrid underlying surface classifier based on fuzzy logic using current consumption of mobile robot motion

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Introduction: *One approach to solving navigation and control problems for outdoor mobile robots is to use real-time classification of the underlying surface type over which the robot is traveling. Knowledge of the underlying surface type allows one to use previously known surface characteristics to improve localization accuracy and control algorithms.* ***Purpose:*** *To research applicability of the energy cost of motion for solving the problem of classifying surfaces with different physical properties for a robot with complex kinematics.* ***Results:*** *The analysis of multi-component motion types has shown that the best distinguishing between surfaces is achieved by using the motor current values. A fuzzy classifier is synthesized on data that was grouped according to the criterion of the most impactful motor in a selected direction of motion. We then compare the classifier with machine learning methods. Machine learning algorithms outperform the fuzzy logic in terms of average accuracy, but fall behind in terms of generalization. We propose a fuzzy logic – machine learning hybrid in order to preserve the generalization of the fuzzy classifier and improve the accuracy of surface detection by considering more patterns using machine learning methods. The proposed method for analyzing and classifying data allows us to distinguish with high accuracy between surfaces differing in power consumption levels, including those that are formed due to different surface properties.* ***Practical relevance:*** *Results of the research can be employed in developing either a standalone surface classifier or a component of a complex classifier with varying input data types.*

Keywords *— underlying surface classification, hybrid methods, machine learning, fuzzy logic, decision trees, gradient boosting, mobile robotics, motor consumption current analysis.*

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Introduction

One approach to solving navigation and control problems for outdoor mobile robots is to use real-time classification of the underlying surface type over which the robot is traveling. They traverse different surfaces such as soil, sand, stones, snow, ice, concrete, asphalt and others.

Knowledge of the underlying surface type allows previously known surface characteristics to be used to improve localization accuracy and control algorithms. In this case, controlling the mobile robot using internal parameters and coordinates measured by the robot's sensitive elements is particularly valuable. This approach provides greater autonomy and is sometimes the only technically feasible option. To obtain additional information about the underlying surface, it is proposed to determine its type using the robot's internal measured variables. In this case, the classifier will consider previously known surface characteristics, including their impact on the robot. This will provide additional information for solving problems related to local navigation, design adaptation, and control algorithms, resulting in a qualitatively different outcome.

In our opinion, there are four main approaches to solving the surface classification task, which vary according to the information given to the classifier and the way the surface affects the robot's movement.

The first approach is to use visual information about the surface. This way we can obtain indirect information about the surface parameters. For example, roughness, color, and uniformity. Cameras are used as sensors. In this case, the images of the surface can be taken in front of the robot [1] or under its wheels [2]. The main advantages of this category are the independence from the design of the mobile robot and the ability to determine the type of surface before moving on it. The disadvantages are dependence on sensor operating conditions (the influence of lighting, dust, precipitation, vibrations) and the inability to directly determine the characteristics of the surface, which are important parameters for solving other problems. Therefore, in most studies, this method is fused with methods based on other data. For example, visual data is combined with inertial sensor readings as in [3, 4] or with acoustic signals corresponding to the surfaces under investigation [2, 5]. In [3] the classification accuracy using the visual method ranged from 73.6 to 96.4% depending on the method applied.

The second approach is to identify the surface topography during locomotion. In this case, we obtain surface characteristics directly through the robot's interaction with it. The topography can be derived through the vibration of the mobile robot's structure components. For this purpose, acoustic sensors (microphones) [6] and inertial systems mounted on the robot's actuators (Inertial Measurement Unit — IMU) [7–9] can be used. To develop a classifier, initial tests are necessary to collect data on the surfaces where the robot will operate. Hence, classification is based on comparing with known test data. In [10] there are results of surface classification by different types of input data, including the surface topology obtained by IMU. It shows that this approach achieves high accuracy (>80%) for rough surfaces and low accuracy (about 33–63%) for smooth and soft surfaces. A tapered spring attached to a mobile robot can act as a sensor for vibration detection [11]. Ideologically, this principle can be implemented for the robot's suspension. Displacement of magnets fixed on the spring is determined by hall sensors to measure the spring vibration. At the same time, the acquired vibration data is used for subsequent AI-based classification with an accuracy ranging from 80 to 89% on the trained data and from 77 to 89% on new data [11]. Another direct topography identification method is based on the use of surface-reflected sound signals of different frequencies emitted from the robot [12]. Here, the average classification accuracy on three types of surfaces — grass, sand, and concrete — was 97.33%.

In general, this approach is widely used. It provides valuable information about surface relief and allows to classify it with high accuracy. The topography is an important characteristic of the surface that is often used to evaluate its impact on the mobile robot. Nevertheless, this can only be achieved by relying on the previously derived dependencies between the relief and the robot's motion. One of the drawbacks of using this approach is the reduced accuracy when dealing with smooth and soft surfaces.

The third approach is to use information about the propulsor's contact force with the surface. In this case, the reaction forces at the contact points are measured. Therefore, surface characteristics directly obtained through robot-ground contact. It is widely studied by terramechanics. In this case, F/T sensors are primarily used. They can be installed on the propulsion system either separately or as a combination of several dozens of sensors. In general, this approach is widespread for walking robots. In [13, 14] an average accuracy of 91–93% is obtained depending on the used approach to data preparation and analysis. Applying this method for a walking robot [15] using a special motion resulted in classifying surfaces with an average accuracy ranging from 62.00 to 97.50% depending on the number of considered surface features and on the chosen machine learning model. In [16] arrays of F/T sensors on a flex circuit are placed on the C-shaped legs of the robot. A classifier performs better on soft surfaces (grass, gravel, sand) with accuracies of 92–97% than on hard surfaces (concrete, tile) with accuracies around 70%.

The advantage of this approach lies in the direct focus on the robot's contact with the surface. Consequently, it is possible to determine its characteristics. For example, for wheeled robots [17–19] this approach allows for the determination of underlying surface parameters such as surface cohesion and internal friction angle. However, additional information must be used to evaluate the direct effect on the robot. The disadvantages are the difficulties in determining the surface and the design limitation of installing such sensors.

The fourth approach — we propose to use information about the energy cost of motion. This information characterizes the impact of the surface on the robot, rather than the surface itself. The power consumption can be evaluated using basic sensors integrated into the platform, such as the draw current and voltage sensors of the actuators. Therefore, in essence, we use internal measurable states of the system. Current sensors of motors are primarily used. In this case for DC motors, this information can be applied to calculate the torque applied to each wheel [20]. Often this information is combined with information from other sensors, such as encoders [21]. In [10], the values of motor voltages and currents are used to classify 5 types of outdoor surfaces using a neural network: gravel, grass, sand, pavement, and dirt. The average accuracy on motor currents in the time domain was 56.9%. The classifier on motor currents performed best on smooth surfaces with accuracies in the range of 76–83%. Motor current was shown to be the best parameter for sand identifying among all other methods.

However, most often, the energy-based approach is used not for surface classification tasks, but for obtaining the parameters affecting the motion like rolling resistance, wheel slippage [16, 18, 22]. The advantage of this method is the ability to evaluate the surface impact on the robot directly. This is important to designing effective control systems. The disadvantages are: the difficulty in identifying the surface topography, dependence on robot kinematics and control actions such as speed and type of motion.

An analysis of the advantages and disadvantages of the above approaches shows that none of them can solve the surface classification problem with high accuracy for a wide class of robots and a large number of underlying surfaces. This conclusion is supported by results presented in a study [10], where an analysis of various sensor data groups showed the prevalence of different methods for different surface types. Consequently, the relevance of the study is confirmed by the lack of a general methodology. At the moment, there are only specific solutions to this problem with predetermined conditions. In terms of control algorithms, the proposed approach, that is based on direct evaluation of the surface's effect on the robot, will solve the problem of surface classification while also allowing to directly control the robot depending on the required character of motion.

However, classifiers based on the fourth approach, that use information about power consumption have not been thoroughly researched. Therefore, this paper focuses on investigating the applicability of these insights to the classification task. The problem is complicated by a complex kinematic structure of the robot and varying motion velocities. The classifier based on this approach can be used in the future in a universal classifier, which will combine different approaches to solving the problem of surface recognition. Of particular interest is the study of such a classifier on surfaces with a wide range of physical parameters, including those that are weakly correlated with power consumption.

Experimental setup

The schematic design of the experimental setup is shown in Fig. 1. The Festo Robotino 1.6 mobile robot is used for the experiments (Fig. 1, *a*).

This robot has a wheelbase on omni-wheels, which allows it to move in any direction without rotating the entire structure. Such wheelbase makes the classification task more challenging due to the mutual influence of the wheels during movement. There may be situations where the frictional force of the wheel does not align with the vector of linear motion of the wheel. This effect can be compared to lateral slippage on a slippery or inclined surface, as seen in outdoor robotics. The use of a robot with an omnidirectional platform is a more general and complex case for solving the classification task.

The robot is controlled through velocities in the local coordinate system. It is equipped with three DC motors. Each motor has a current sensor and a shaft-mounted encoder. The mobile platform moves on a test site with interchangeable types of underlying surface: type 1 — soft smooth (gray); type 2 — hard rough (green); type 3 — hard smooth (table) (Fig. 1, *b*). Each surface has a different effect on the robot's motion. Note that type 1 and type 2 surface have close values of power consumption parameter, but it is formed due to different surface properties (gray — softness, green — topography). Similar surfaces were also researched in [21, 23, 24].

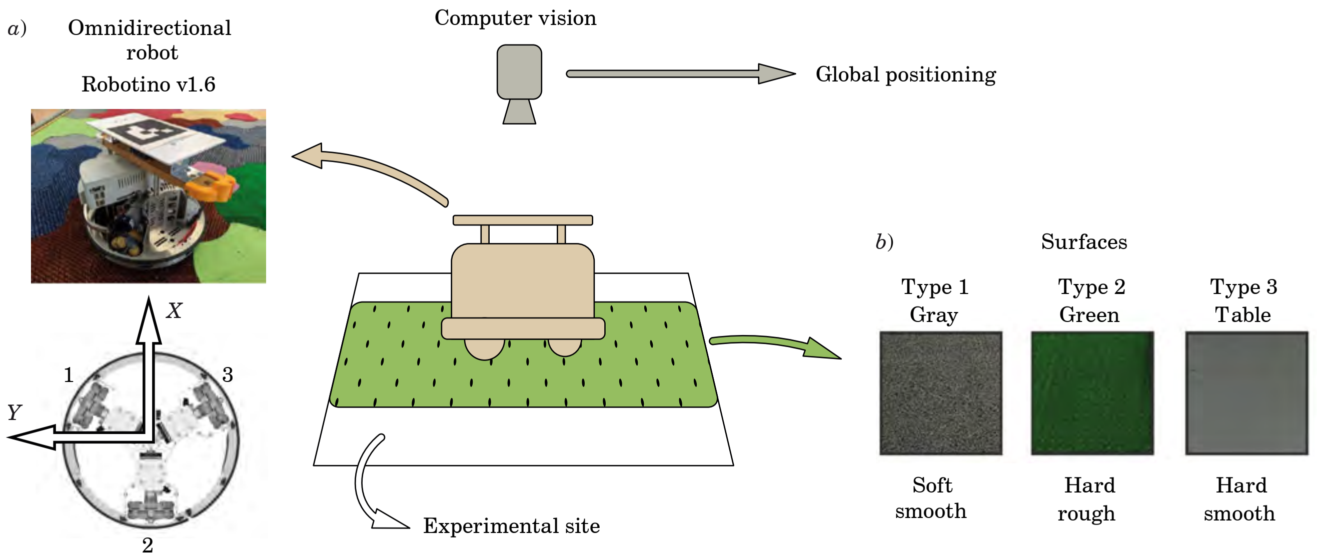
Consequently, the following control parameters are varied in the experiments:

— underlying surface type (3 surface types);

— the amplitude of the robot's velocity (from 0.1 to 0.3 m/s);

— direction of robot‘s speed (26 directions, including rotational component).

During the experiment, the following sensor system data are read from the robot at a sampling rate of 0.1 s: wheel angular velocity $\{\omega_i\}$ and consumption current for each motor $\{I_1, I_2, I_3\}$. It is not possible to get a direct measurement of a motor's voltage on the Festo Robotino 1.6. Therefore, we will solely



■ ***Fig. 1.*** Experimental setup: *a* — appearance, coordinate system and motor arrangement of the Festo Robotino 1.6; *b* — surface types rely on information from current sensors to solve the classification task based on power consumption. Additionally, the following parameters are calculated using the values of the current draw [21, 23]:

— currents along the mobile platform movement axes $\{I_x, I_y, I_\varphi\}$:

$$\begin{pmatrix} I_x \\ I_y \\ I_\varphi \end{pmatrix} = \begin{pmatrix} -\frac{2}{3}\cos(\alpha-\theta) & -\frac{2}{3}\sin(\alpha-\theta) & \frac{2}{3}\cos(\alpha+\theta) \\ -\frac{2}{3}\sin(\alpha-\theta) & -\frac{2}{3}\cos(\alpha) & \frac{2}{3}\sin(\alpha-\theta) \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix} \begin{pmatrix} I_1 \\ I_2 \\ I_3 \end{pmatrix};$$

— forces along the axes $\{F_x, F_y\}$ and robot torque M_Ω:

$$\begin{pmatrix} F_x \\ F_y \\ M_\Omega \end{pmatrix} = \frac{1}{r} \begin{pmatrix} -\cos\left(\frac{\pi}{6}\right) & \sin(0) & \cos\left(\frac{\pi}{6}\right) \\ -\sin\left(\frac{\pi}{6}\right) & \cos(0) & \sin\left(\frac{\pi}{6}\right) \\ L & L & L \end{pmatrix} \begin{pmatrix} M_1 \\ M_2 \\ M_3 \end{pmatrix};$$

— total current consumption of the motors

$$I_\Sigma^{motor} = |I_1| + |I_2| + |I_3|;$$

— total current along the platform movement axes

$$I_\Sigma^{axes} = |I_x| + |I_y| + |I_\varphi|;$$

— torques on the motors $\{M_1, M_2, M_3\}$:

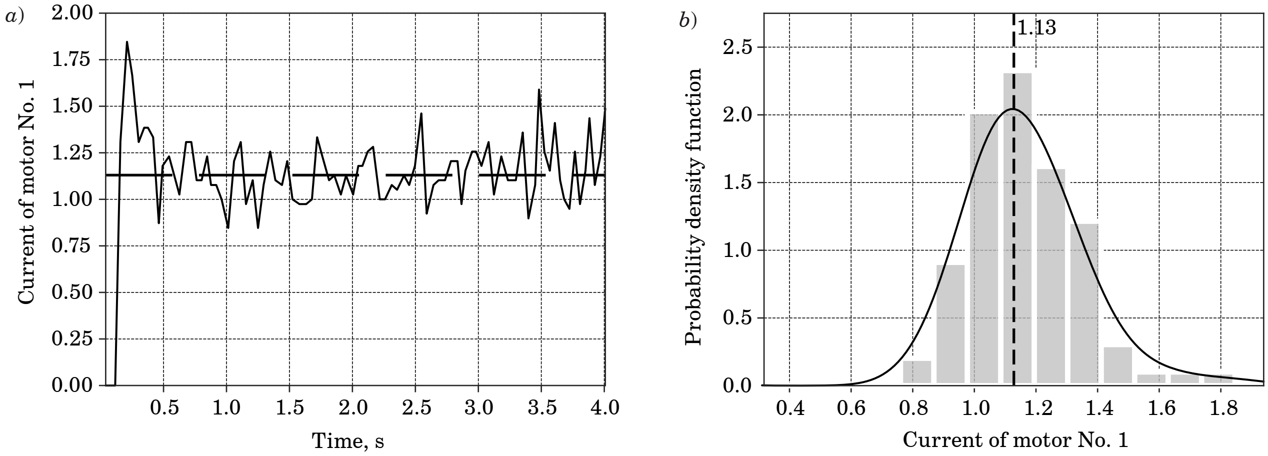
$$M = \frac{UI}{\omega}, \; U = IR + C_e\omega,$$

where φ is the rotation angle of the robot's wheels ($\varphi = 30°$); α is the rotation angle of the robot; r is the radius of the wheels ($r = 40$ mm); L is the distance from the center of the robot to the wheels; U is the motor voltage; I is the motor current; R is the motor winding resistance; C_e is the electrical coefficient of the motor.

Research methodology

At the beginning, data from a single experiment was analyzed. This analysis showed that in static operating mode, the momentary values fluctuate strongly. An example of motor current consumption values is shown in Fig. 2, *a*. Fluctuations arise due to measurement noise and weak homogeneity in the underlying surface of the same type. The analysis of the density of values indicates that the data distribution adheres to the bell curve (Fig. 2, *b*). This implies the necessity to analyze not momentary readings, but the distributions of values for different types of surfaces within one experiment. For easier analysis, the distributions will be presented in the form of box plots. For each experiment, boxes are plotted using the motor current values and all derived values described in the previous section for all types of surface.

In the box plots, we analyze the positions of median values, boundary intervals, their spread, and intersections with other boxes. The upper boundary of the interval corresponds to the value below which 75% of all data falls, known as the 75th percentile, while the lower boundary corresponds to the 25th percentile. Qualitative analysis of box plots showed that, for each type of motion, a specific parameter (such as motor currents, forces along axes, etc.) was most effective in distinguishing the surface. In particular, for motion along the X-axis in the local coordinates of the robot, the best possibilities for surface identification are giv-



■ ***Fig. 2.*** Value current of motor No. 1 when driving on a gray surface along the X-axis at a commanded velocity of 0.2 m/s: *a* — values against time; *b* — histogram and probability density function en by currents of motor No. 1 and 3, current along the X-axis, and force along the X-axis (Fig. 3).

The next step is to quantitatively verify the conclusions derived from the qualitative analysis. For each experiment we evaluate the intersections of value intervals for all types of surfaces. First, we select the reference interval and label it as X. Next, we label as y the interval for the surface, which intersects a portion of X.

We identify possible interval locations in order to calculate quantitative representations of intersection.

A. The upper and lower bounds of one interval are above or below the corresponding bound of the other interval:

$$y \cap X = \begin{cases} \dfrac{X_{75} - y_{25}}{X_{75} - X_{25}} \cdot 100\%, \text{ if } y_{75} > X_{75}, y_{25} > X_{25}; \\ \dfrac{y_{75} - X_{25}}{X_{75} - X_{25}} \cdot 100\%, \text{ if } y_{75} < X_{75}, y_{25} < X_{25}. \end{cases}$$

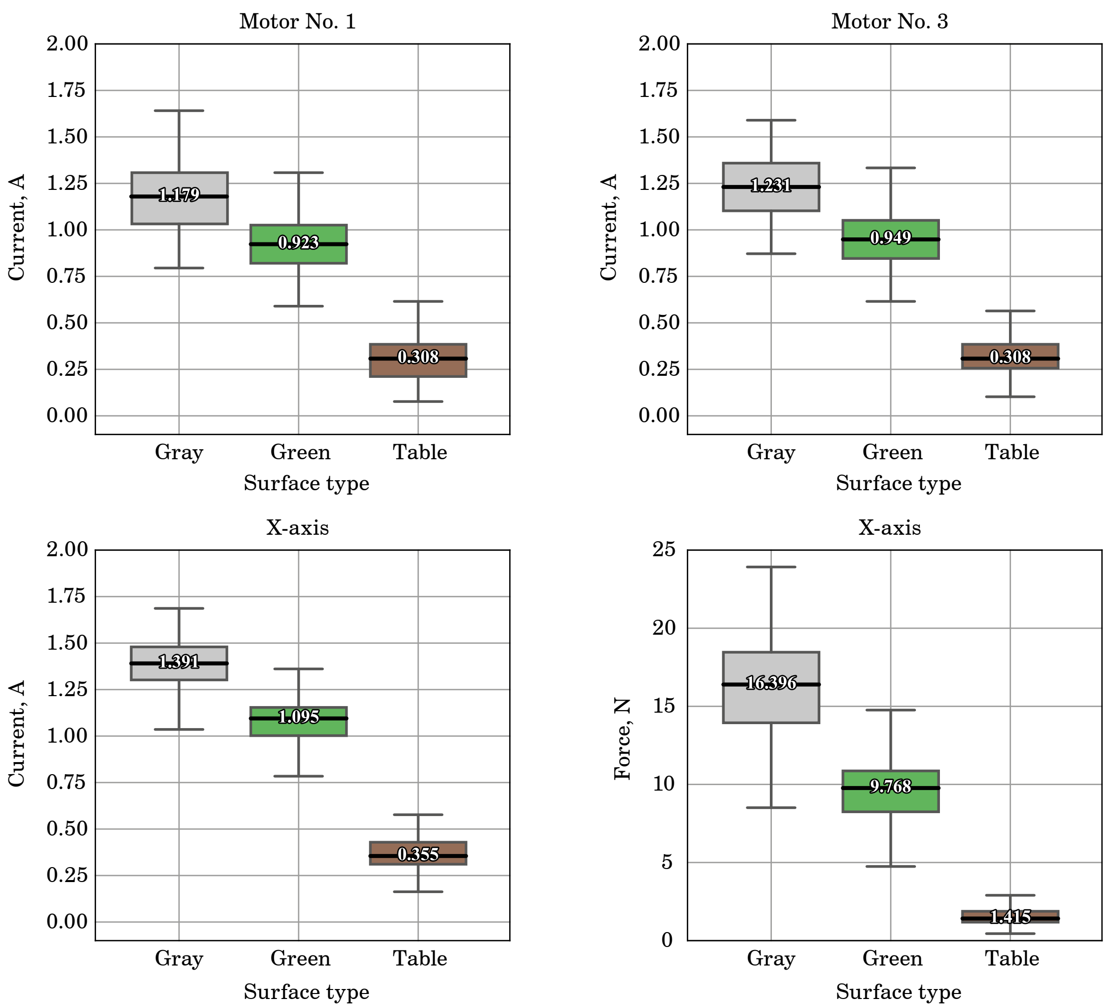
B. One of the intervals lies entirely within the boundaries of the other interval. The values are taken with a negative sign to distinguish them from the intersections of the first case:

$$y \cap X = \begin{cases} -\dfrac{X_{75} - y_{25}}{X_{75} - X_{25}} \cdot 100\%, \text{ if } y_{75} < X_{75}, y_{25} > X_{25}; \\ -100\%, \text{ if } y_{75} > X_{75}, y_{25} < X_{25}. \end{cases}$$

C. A value of 0% means that there is no intersection for this pair of surfaces, i. e. we can clearly distinguish them.

For the experiment, from which the data was previously used for box plots earlier (see Fig. 3), the derived numerical representations of the intersections are shown in Table 1.

Quantitative analysis of the range intersections for different parameters confirms the qualitative analysis and shows that the intersection values remain stable as the amplitude of the robot‘s velocity



■ ***Fig. 3.*** Box plots for currents of motor No. 1 and 3, current along the X-axis and force along the X-axis at a commanded velocity of 0.1 m/s

■ ***Table 1.*** Intersection values for movement along the X-axis for currents of motor No. 1 and 3, current along the X-axis and force along the X-axis

Amplitude	Current , %,									Force along the X-axis, %		
	of motor No. 1			of motor No. 3			along the X-axis					
	Green-gray	Table-green	Table-gray	Green-gray	Table-green	Table-gray	Green-gray	Table-green	Table-gray	Green-gray	Table-green	Table-gray
100	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
200	**14**	**0**	**0**	**30**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
300	74	**0**	**0**	62	**0**	**0**	**34**	**0**	**0**	40	**0**	**0**

rises. The exception is the pair of two high power consuming green-gray surfaces, where an increase in amplitude results in an increase in the intersection value. Similar conclusions are obtained for other simple motion types, i. e., for motion along the Y-axis or for rotation.

The following conclusions were also drawn during the analysis.

1. For experiments where the velocity is multicomponent, i.e. a combination of linear motions with the possible addition of rotational motion, the use of motor currents leads to better results in distinguishing between surfaces compared to the use of currents and forces along the axes. As a result, the motor current was chosen as the key parameter for the subsequent analysis.

2. It is worth selecting a motor with a greater impact in a particular type of motion in order to obtain better surface identification results by motor current consumption values. The experiments show that the motor impact depends on the direction of motion. It is derived from the kinematics of the robot.

3. In the ideal scenario, it would be advantageous to describe patterns for classifying surface types across all motion types investigated. However, with an increase in the number of directions and amplitudes of motion, the number of identified patterns will become excessively large. Also, the need to constantly explore new motion types makes the classifier inflexible. For these reasons, we group the motion types based on the principle of greater motor impact in the motion.

The main disadvantage of grouping experiments by motion type is the increased heterogeneity of the data compared to individual motions. This obviously leads to a loss of accuracy in surface classification. A major concern with this approach is the selection of an appropriate discretization step to form direction-based motion groups. It is clear that reducing the step will lead to higher classification accuracy, but will force the developers to synthesize more rules to identify surfaces. The study favored maximum data aggregation by direction of motion. In each group, current values of one motor prevail over the others. Consequently, 13 motion groups are derived (including the rotational component). In our opinion, this number of groups represents the minimum requirement for adequate surface classification.

An example is provided in Table 2, that displays the median and standard deviation values of a current consumption calculated for the motor No. 3 by motion groups. The lines in bold are those for which the current sensor readings of the third motor show good separability. Derived data confirms the assumption that a particular motor prevails for identifying surfaces depending on the motion direction.

Figure 4 shows motor current box plots across all surfaces for each type of motion. The number of the motor that provides the most accurate distinguishing between surfaces for a given motion type is indicated above each plot. Thus, the figure shows the best dependencies for classifying surfaces in our case. It is observed that poor surface separability in particular motions is caused by the prevailing impact of the motor No. 2.

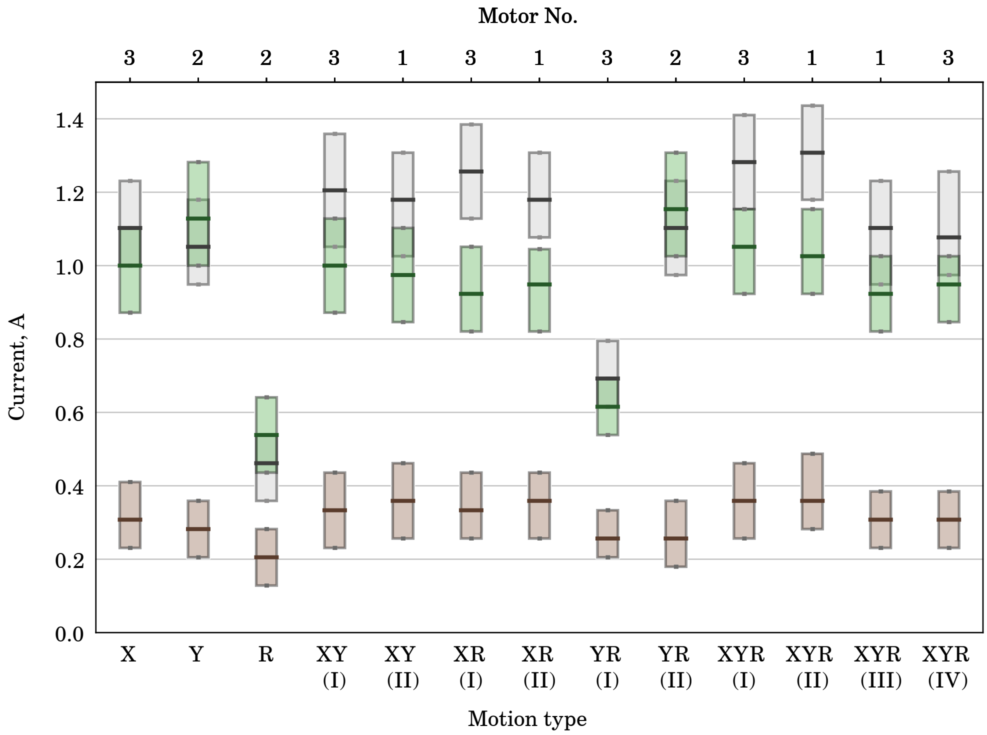
Considering all the analyses, we estimated a lower bound for the accuracy of surface classification based on the obtained patterns. For this purpose, the following formula was applied:

$$\underline{accuracy} = \frac{1}{n_{dirs}} \sum_{i=1}^{n_{dirs}} \frac{1}{3}\left(\beta^i_{gray} + \beta^i_{green} + \beta^i_{table}\right),$$

where n_{dirs} — is the number of motion groups; β_x — accuracy of surface x, i. e. the part of the range of surface x that does not intersect with the ranges of the other surfaces.

■ ***Table 2.*** Median and standard deviation values of consumption current of motor No. 3 by motion groups

Direction in the local coordinates	Motion group	Current of motor No. 3					
		Gray		Green		Table	
		Mdn	σ	Mdn	σ	Mdn	σ
X+, X–	X	**1,103**	**0,039**	**1,000**	**0,032**	**0,308**	**0,018**
Y+, Y–	Y	0,564	0,022	0,615	0,017	0,256	0,013
X+ Y+, X– Y–	XY (I)	**1,205**	**0,053**	**1,000**	**0,047**	**0,333**	**0,034**
X+ Y–, X– Y+	XY (II)	0,513	0,098	0,436	0,068	0,205	0,017
R+, R–	R	0,385	0,016	0,410	0,017	0,205	0,012
X+ R+, X– R–	XR (I)	**1,256**	**0,036**	**0,923**	**0,024**	**0,333**	**0,014**
X+ R–, X– R+	XR (II)	0,923	0,163	0,795	0,155	0,231	0,024
Y+ R+, Y– R–	YR (I)	0,692	0,019	0,615	0,020	0,256	0,012
Y+ R–, Y– R+	YR (II)	0,026	0,004	0,077	0,006	0,000	0,007
X+ Y+ R+, X– Y– R–	XYR (I)	**1,269**	**0,038**	**1,051**	**0,031**	**0,359**	**0,023**
X– Y+ R+, X+ Y– R–	XYR (II)	0,128	0,009	0,051	0,009	0,026	0,007
X– Y+ R–, X+ Y– R+	XYR (III)	0,487	0,018	0,462	0,017	0,205	0,016
X– Y– R+, X+ Y+ R–	XYR (IV)	**1,077**	**0,038**	**0,949**	**0,025**	**0,308**	**0,013**



■ ***Fig. 4.*** Box plots of motor current on three surfaces depending on the direction of motion (color indicates surface types, gray and green accordingly surfaces title, brown for table)

$$\beta_x^i = 1 - \sum_y y_i \cap x_i .$$

In this case, the minimum classification accuracy is estimated to be 79.2%.

Fuzzy classifier

In this paper, fuzzy logic was used to solve the surface classification problem. Our decision was made based on the qualitative and quantitative analysis of the intersection of motor current intervals across the surfaces, without considering the median value's position. We have chosen to use fuzzy logic because it offers several advantages in this case:

— easily handles data represented as sets;

— flexible rule generation for different motion types;

— based on the degree of membership of a particular value to a set which will help make use of median values later when forming sets;

— suitable for working with tasks that are not well formalized, for example, as in [25].

It is also convenient that the key objectives of implementing fuzzy logic have already been solved in the data analysis section. These objectives include creating input variable sets and formulating the algorithm rules.

In this paper, the Takagi — Sugeno fuzzy algorithm was chosen because it eliminates the need for deriving membership functions at the classifier's output. This choice is based on the specific classification task we addressed. The input of the classifier is the consumption current values of each robot's motor I_1, I_2, I_3, the values of commanded X-axis speed, Y-axis speed, and commanded rotation speed ω. Numerical velocity values do not play a role in the classification process. Rather, they function as logical variables in the classifier to identify the direction of motion. An example of input membership functions for motor current values is shown in Fig. 5.

In this case, the membership functions are constructed as Gaussians, because at the analysis stage the values from the current sensors within one experiment adhere to a normal distribution. The values of medians and standard deviations for the membership functions are taken from the data analysis section.

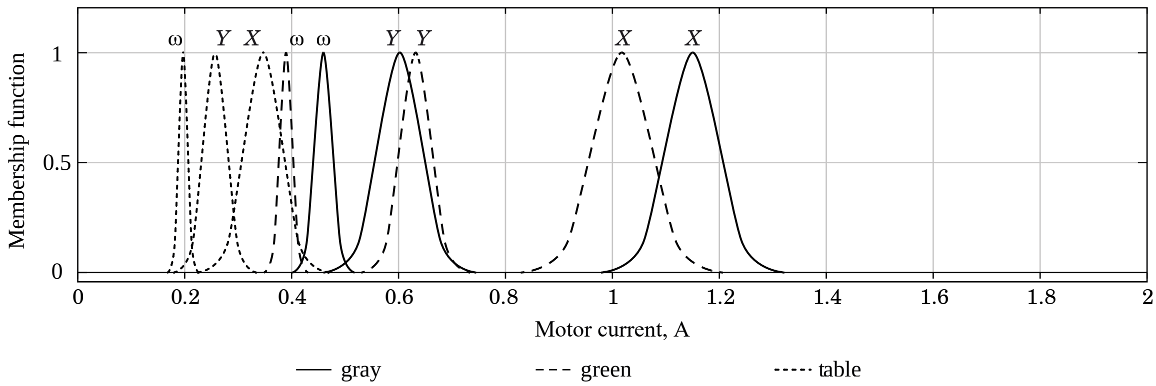
The classifier's output variable represents the degree of membership of motor current values to each surface, using a one-vs-all approach.

Evaluation of the fuzzy classifier

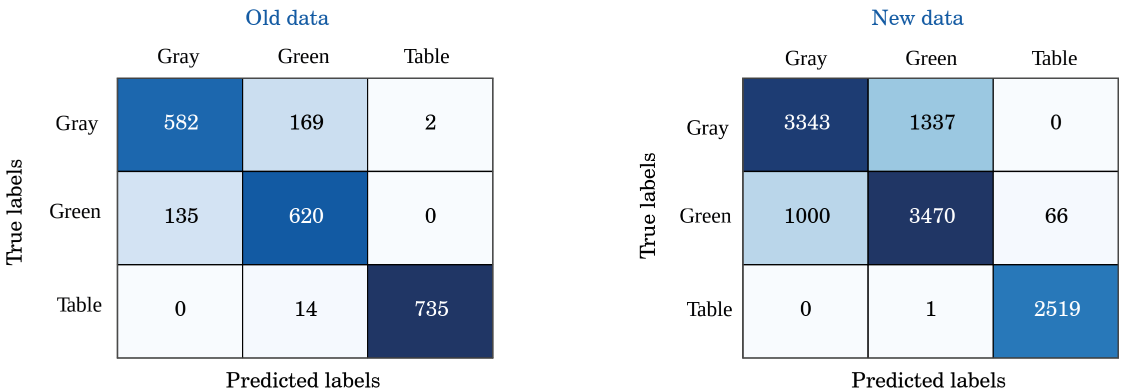
The evaluation of classifier accuracy is performed in two steps:

1. Testing the classifier on the original data that we used in the analysis phase to derive rules for distinguishing surface (*old data*).

2. Testing the classifier on separately gathered *new data*. New dataset contains more motion direc-



■ ***Fig. 5.*** Example of input membership functions of a fuzzy classifier



■ ***Fig. 6.*** Confusion matrices for results obtained with the fuzzy classifier tions and amplitudes compared to the *old data*. This test is necessary to evaluate the classifier's generalization in case of variable data.

Accuracy will be used as the key metric:

$$accuracy = \frac{\text{correct predictions}}{\text{all predictions}}.$$

The accuracy on *old data* is expected to be higher than the previously estimated lower bound of 79.2%. The obtained accuracy on the two datasets is shown in the confusion matrices in Fig. 6.

As a result, the classifier showed an average accuracy of 85.8% (gray — 77.3%, green — 82.1%, table — 98.1%) on the *old data*. After switching to the *new data*, the accuracy dropped to 79.5% (gray — 77.0%, green — 72.2%, table — 97.4%). The most errors in both cases are made between the gray and green surfaces as the sensor system readings on these particular surfaces are partially similar in the process of a motion.

Machine learning

The performance of the fuzzy classifier is compared with machine learning models, which showed high quality of performance for the multiclass classification task.

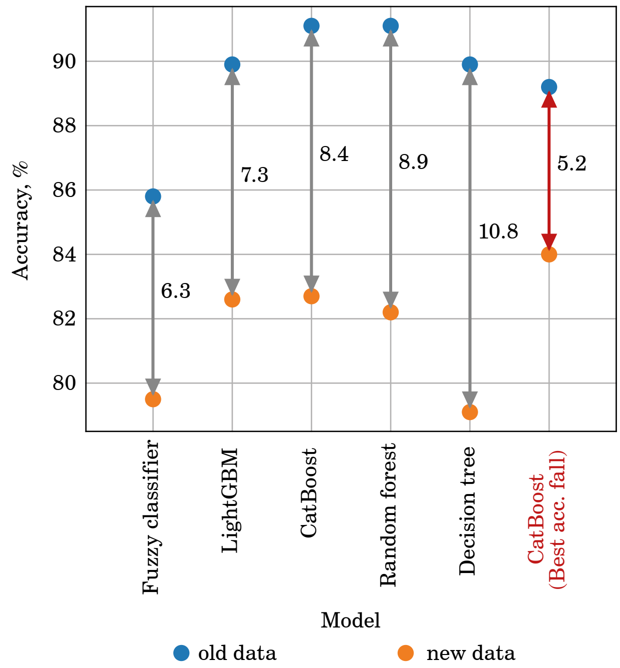
Based on a review [26] that identifies advantages, disadvantages, and applications of various machine learning methods used in classification tasks, we have chosen the following models that are balanced in terms of accuracy and learning speed: decision tree [27], random forest [28], LightGBM [29] and CatBoost [30]. All models are trained on the same data set that used to create the fuzzy classifier.

The algorithms are trained and validated on the initial set *old data*. Train — validation — test split ratio is 60–10–30%. Then, like a fuzzy classifier, the algorithms are tested on *new data*. The accuracy of the algorithm is evaluated similarly to that of the fuzzy classifier. During training on *old data*, hyperparameters are selected from the parameter grid based on the best accuracy criterion for each model. The accuracy score for hyperparameter tuning was calculated on train data using 5-fold cross-validation.

The results of the two-step tests are shown in Fig. 7. From the figure we can see that:

— The maximum accuracy of 91.1% on *old data* and the maximum accuracy of 82.7% on *new data* was shown by the gradient boosting algorithm CatBoost. Almost similar levels of accuracy are achieved with random forest.

— The fuzzy classifier shows the smallest accuracy fall of 6.3% between results for both data sets. This indicates its better generalization compared to machine learning algorithms tuned for the best accuracy.



■ ***Fig. 7.*** Results of classifier accuracy evaluation on two datasets

— The accuracy fall in the range of 7 to 8%, comparable to the fuzzy classifier, appears only in the CatBoost and LightGBM boosting algorithms. Meanwhile, the average accuracy of the fuzzy logic based algorithms is lower by about 8% compared to the boosting algorithms, with a comparable accuracy fall. In other cases, an accuracy fall of over 8% is observed.

Similarly to tuning hyperparameters with the best accuracy criterion, machine learning algorithms are tuned for greater generalization in order to get a smaller accuracy fall when transitioning to *new data*. The CatBoost model achieved the best results at these hyperparameters, with an accuracy fall of only 5.2%.

Fuzzy logic — machine learning hybrid

The proposed fuzzy classifier, which is based on the identified patterns derived from analysis, demonstrates a generalization that is comparable to the best machine learning algorithm tuned for the same purpose. The reason for this is the design of input sets and rules derived from statistical information. Still, when compared to machine learning algorithms, its overall accuracy is lower because of a significant discretization step for grouping data based on motion direction. With precise tuning of the fuzzy classifier, the accuracy could be comparable to that of machine learning algorithms. However, the synthesis of a large number of rules would require a great deal of time. For instance, currently, the fuzzy classifier has 78 rules, while CatBoost tuned for the best accuracy has 1974 rules.

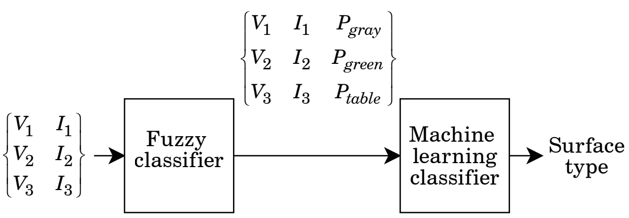
We suggest a solution to use the outputs of the proposed fuzzy classifier as feature inputs for machine learning algorithms. We aim to achieve more precise tuning of the fuzzy classifier while preserving its simplicity and generalization. The structure of the proposed hybrid solution is shown in Fig. 8.

For the hybrid algorithm, we trained the same machine learning methods used in the previous stage.

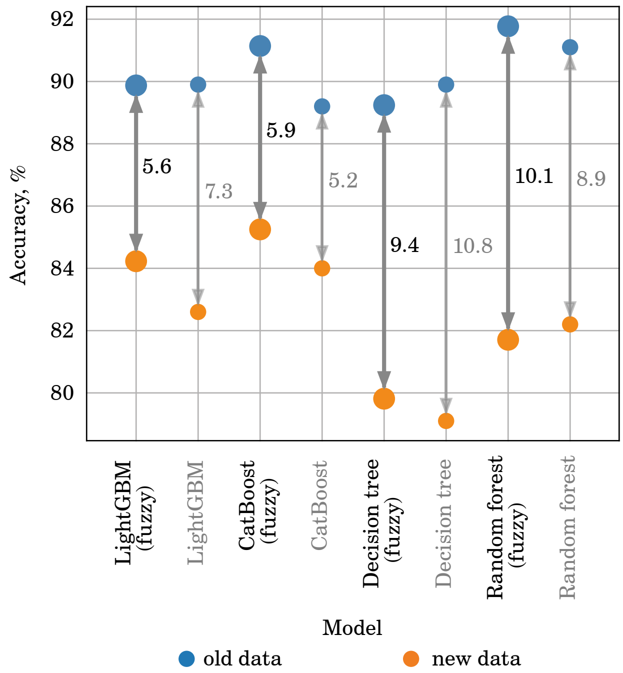
The results of testing the cascade on two datasets and comparing them to methods without fusion with fuzzy logic are shown in Fig. 9. It can be observed that the addition of fuzzy logic as input features gives inconsistent results. It can either increase or decrease the accuracy fall and the average accuracy on different datasets. The best effect is achieved for a hybrid of fuzzy logic and CatBoost. The average classification accuracy increased on both datasets, resulting in a reduction of the accuracy fall compared to the original fuzzy classifier. In comparison with CatBoost, the proposed algorithm showed on *old data* an accuracy comparable to the best accuracy tuning 91.1% (gray — 86.0%, green — 82.6%, table — 100.0%) and an accuracy drop comparable to the best generalization tuning with difference 0.7%. As a result, the proposed hybrid method gave the maximum accuracy on *new data* 85.2% (gray — 83.6%, green — 79.5%, table — 98.9%). Also, the number of rules of the final classifier decreased to 980.

It was confirmed that the output values of the fuzzy classifier are the main parameters that CatBoost uses for surface recognition. For complex gray and green surface types, the fuzzy classifier values are prioritized in CatBoost. Decision tree structure analyses in CatBoost reveal the prioritization of fuzzy classifier outputs as features at first layers in the trees (1–2 layer). In addition, the *feature importance* metric of CatBoost model showed the following feature priority: fuzzy classifier output for gray surface (23.72%), fuzzy classifier output for green surface (20.01%), consumption current of motor No. 3 (17.36%), consumption current of motor No. 1 (16.47%), consumption current of motor No. 2 (13.83%), fuzzy classifier output for table (8.60%).

This set of feature importances confirms the significance of the fuzzy classifier outputs, and also indicates that the model uses motor current values to adjust the final result, thus increasing the average accuracy.



■ ***Fig. 8.*** Fuzzy logic — machine learning hybrid structure



■ ***Fig. 9.*** Results of hybrid method accuracy evaluation on two data sets

Conclusion

The research carried out on resolving the surface classification issue, using an omnidirectional robot as an example, allowes us to draw several conclusions. The analysis of complex multi-component motion types has shown that the best distinguishing between surfaces is achieved by using the motor current values. In this case, it is more appropriate to classify the surfaces based on the readings from the current sensor of the motor with the most impact in the motion process. The impact of the motor derives from the robot kinematics and the selected direction of motion.

During the preparation phase for the classifier implementation, it became evident that the fuzzy logic principles complement the performed analysis of sensor value distribution, including their median and standard deviation values. The quantitative analysis of the values' intersection proves the qualitative analysis and allowes us to assess the classifier's lower limit of accuracy at 79.2%.

The fuzzy classifier is synthesized on data that was grouped according to the criterion of the most impactful motor in a selected direction of motion. This approach reduces a number of fuzzy logic rules. The classifier is subsequently tested on the original (*old data*) and extended (*new data*) data sets. The accuracy is estimated to be 85.8 and 79.5% respectively, with an accuracy fall of 6.3%. The fuzzy classifier is then compared with machine learning methods. In most cases, machine learning algorithms outperform the fuzzy classifier in terms of average accuracy, but loses out in terms of accuracy fall.

In this paper, we propose a fuzzy logic — machine learning cascade in order to preserve the generalization of the fuzzy classifier and improve the accuracy of surface detection by considering more patterns using machine learning methods. The best results are achieved by the hybrid of CatBoost and fuzzy logic. It shows 91.1% accuracy on *old data* and 85.2% on *new data* with a 5.9% accuracy fall. This is the best classification result among all tested methods.

The proposed method for analyzing and classifying data allows us to distinguish between surfaces with different power consumption (gray and table). Moreover, the classifier demonstrates high accuracy in identifying surfaces with similar power consumption levels that are formed due to different surface properties (gray — softness, green — topography).

Compared to [10], the obtained surface classification accuracy on the new data of 85.2% is higher than the average classification accuracy for all surfaces of 56.9% when using only information from motor currents.

The proposed classifier demonstrated comparable classification accuracy on the training data (old data) (gray — 86.0%, green — 82.6%, table — 100%) to the classifier in [21] (gray — 82.1%, green — 88.0%, table — 97.0%). In [21], the authors used an extended vector of sensory information for the classifier, including robot velocities, accelerometer, and gyroscope data. The robot and the underlying surfaces are similar in both cases.

Discussion

Surface classification with subsequent extraction of information about the properties of the surface is one of the main priority tasks for outdoor robots. However, for most local navigation tasks this problem is solved by conducting a preliminary surface analysis and creating a classifier based on the obtained data. This paper raises the problem of a lack of universally applicable approach for solving the classification problem. In continuation, we will focus on the versatility of solving the classification problem based on the proposed data analysis and the classifier construction technique.

Firstly, further research will focus on the possibility of transitioning to a single value that describes the energy cost of motion. This value depends on the kinematics of a mobile robot, direction of motion, rotation speed amplitude, and other relevant parameters. We believe a universal parameter will reduce a number of input features in the classifier.

Secondly, we plan to explore the classification of surfaces across a full range of motor currents or the power consumption parameter. This involves generating new sets and rules for the classifier as the robot navigates, and adapting existing sets and rules to changes in the external environment. Real-time modifications to the classifier will make it a universal solution to the problem of distinguishing between surface types.

Lastly, as this work concentrates on analyzing only the direct power consumption of motion, further research will use additional information to expand the understanding of surfaces' physical properties.

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Синтез гибридного классификатора подстилающих поверхностей на основе нечеткой логики с использованием токовых энергозатрат движения мобильного робота

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Введение: одним из подходов при решении задач навигации и управления мобильными роботами, работающими на открытом воздухе, является использование классификации типа подстилающих поверхностей, по которым перемещается робот в реальном времени. Знания о типе подстилающей поверхности позволяют использовать ранее известные характеристики поверхностей для улучшения точности локализации и алгоритмов управления. **Цель:** исследовать применимость данных об энергозатратах движения для решения задачи классификации поверхностей с различными физическими свойствами для робота со сложной кинематикой. **Результаты:** анализ многокомпонентных типов движения всенаправленного робота показал, что лучшая разделимость поверхностей достигается при использовании значений токов двигателей. При этом классификацию поверхностей целесообразнее осуществлять по значениям тока двигателя, наиболее влияющего на процесс движения. Нечеткий классификатор синтезирован на основе данных, сгруппированных по критерию наиболее влияющего на выбранное направление движения двигателя. Проведено сравнение нечеткого классификатора с методами машинного обучения. Предложен каскад нечеткая логика — машинное обучение с целью сохранить обобщающую способность нечеткого классификатора и улучшить точность определения поверхностей через учет большего количества закономерностей с помощью методов машинного обучения. Предложенная методика анализа данных и метод классификации позволяют с высокой точностью разделять поверхности, отличающиеся по энергозатратам, в том числе сформированным за счет разных параметров поверхности. **Практическая значимость:** результаты исследований могут быть использованы как для создания самостоятельного классификатора поверхностей, так и в рамках комплексного классификатора с использованием разных видов входной информации.

Ключевые слова — классификация подстилающих поверхностей, гибридные методы, машинное обучение, нечеткая логика, деревья решений, градиентный бустинг, мобильная робототехника, анализ токов потребления.

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