RESEARCH OF THE POSSIBILITY OF APPLYING CASCADED FUZZY ALGORITHMS TO THE PROBLEM OF SURFACE CLASSIFICATION

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Introduction

Autonomous mobile platforms have to identify the underlying surface to adapt to conditions of movement, because of surfaces' properties that affect the nature of the robot's movement. Classification of underlying surfaces can be implemented with the help of computer vision or using information about the accelerations of the robot, vibrations in its structures, feedback from tactile sensors, etc. In this paper we will research an approach to surface recognition using the readings of current consumption sensors of mobile platform motors.

There is a possibility to increase accuracy and performance of method by combining several algorithms to a composition. A proper combination of individual classifiers' results helps to obtain better accuracy compared to each classifier separately. Faster performance is achieved by avoiding parts of algorithms in the composition if desired accuracy is surpassed by previous steps. According to this principle, a cascade of classifiers will be built in this paper.

Robot and data

The robot Festo Robotino 1.6 is used for data gathering in the experiments. It is equipped with three DC motors. The consumption current values for each motor are measured by internal sensors of the robot. Additionally, the current values along the axes of the mobile platform are calculated using the formula described in [1]:

$$\begin{bmatrix} I_x \\ I_y \\ I_\phi \end{bmatrix} = R \cdot \begin{bmatrix} -\frac{2}{3}\cos(\alpha-\theta) & \frac{2}{3}\sin(\alpha) & \frac{2}{3}\cos(\alpha+\theta) \\ -\frac{2}{3}\sin(\alpha-\theta) & -\frac{2}{3}\cos(\alpha) & \frac{2}{3}\sin(\alpha+\theta) \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \cdot \begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} \tag{1}$$

where I_x, I_y – the currents along the X, Y axes of the mobile platform in the local coordinate system, I_φ – rotation current of the mobile platform in the local coordinate system, R – the radius of the wheels ($R = 40\ mm$); α – the angle of rotation of the robot, φ – the angle of rotation of the wheels of the robot ($\varphi = 30°$), I_{1-3} – consumption currents of 1-3 motors.

Total current of the motors and total current along the axes of the mobile platform are calculated using the following formulas:

$$I_\Sigma^{motor} = |I_1| + |I_2| + |I_3| \tag{2}$$

$$I_\Sigma^{axes} = |I_x| + |I_y| + |I_\phi| \tag{3}$$

where I_Σ^{motor} – the total current of the motors, I_Σ^{axes} – the total current along the axes.

Previously mentioned values are collected from the robot while it is driving on one of three types of surfaces: *Type 1* – soft, partially smooth, rubber material, *Type 2* – hard spiky surface with loose filling, *Type 3* – flat wood surface. In each experiment, the robot moves across only one type of surface. Robot's motion vector is determined by commanded velocities along the axes in local coordinate system. A complete set of the vectors is defined by combinations of speeds: along the axis $X = \{100, 200, 300\}\ mm/s$; along the axis $Y = \{100, 200, 300\}\ mm/s$; of the rotation $\varphi = \{20, 40\}\ °/s$.

Box and whiskers plots are built for all surfaces for each experiment to estimate parameters distribution. The values of median, 25 and 75 percentiles, maximum and minimum values of the parameters are used to find dependencies and to subsequently develop rules for distinguishing between surface types. In previous work [2] rules were composed separately for each movement's component without considering alterations in parameter's distribution with different speed amplitudes within one movement direction. However, if surface classifier will be synthesized while considering all found patterns and movements' variants, the number of rules in the classifier will become massive and the ability to quickly interpret and debug the algorithm will be lost. To cover all motion variations with fewer rules, the data is merged by direction of movement. In this paper, two groups of directions of movement are defined, as shown in the Figure 1:

Group No. I – movements with the same amplitude signs along the *axes X, Y*;

Group No. II – movements with different amplitude signs along the *axes X, Y*.

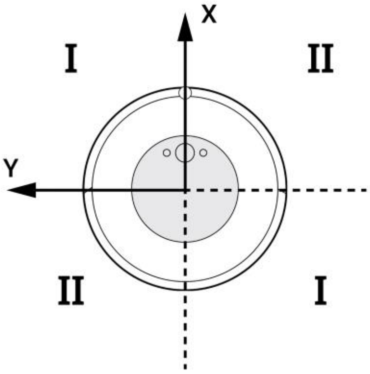

Fig. 1. Quarters in the coordinate system of the robot

Rules that will be used to distinguish surfaces are derived from the resulting merged data. Rules are created for the following parameters: motors' consumption current, currents along the robot's axes, total currents of the motors and total currents along the robot's axes.

Classifier

The classifier is based on a fuzzy algorithm with the implementation of output on the Takagi-Sugeno mechanism. This mechanism allows you to get the output of linear membership function or a constant. This is suitable for the classification task, since the output value does not require additional transformations. Input of the classifier is fed with the values of commanded speeds on the X-axis, Y-axis and rotation ω. Depending on the selected parameters, the input is additionally fed with consumption current values of each robot's motor I_1, I_2, I_3; current values along the axes of the mobile platform I_x, I_y, I_ϕ; values of total currents I_Σ^{motor}, I_Σ^{axes}. Then a correspondence is established between the input numerical value and the value of the membership function for each of the described sets of parameters. The membership functions in this case are constructed as Gaussian distributions using the values of medians and standard deviations that are specified in the rules. The rules developed during the data analysis are transformed into the following construction: *"if A and B and ... then the Type of Surface"*. The output is processed as a transition from a discrete set of crisp values to a single specific crisp value, which in this case is the type of surface. At the output classifier shows the probability of detection for each type of surface from 0 to 1.

To improve the accuracy of surface recognition a cascade of algorithms is created. It combines the results of classifiers by motors' currents, currents along axes, and total currents as a weighted sum.

$$P_x = P_{mc_x} \cdot \omega_{mc_x} + P_{ac_x} \cdot \omega_{ac_x} + P_{total_x} \cdot \omega_{total_x} \tag{4}$$

where P_x – the probability of underlying surface belongs to the type x, P_{mc_x} – the output of the motor's currents classifier for the surface of x type, ω_{mc_x} – the weight of the output of the motors' currents classifier for the surface of the type x. Likewise, for ac – currents along the axes of the robot, $total$ – the total consumption current of the robot motors and the total current along the axes of the robot.

Motors' currents and axes' currents classifiers are used to increase the overall accuracy, therefore, for each surface they are assigned a weight equal to 0.33. Total currents classifier for surfaces *Type 1*, *Type 2* is assigned a weight equal to 0.1, for surface *Type 3* – 0.8, since the main task of this classifier is to separate the *Type 3* surface from all the others.

During individual tests for each classifier, it was revealed that motors' currents classifier shows greater overall accuracy compared to the other two classifiers. Therefore, axes' currents and total currents classifiers are engaged only if motors' currents classifier show less than 75% probability of surface detection. Otherwise, to improve performance, the type of underlying surface is determined only by the output of the motors' currents classifier.

The output of the cascade classifier is the type of surface that has the highest detection probability. The structure of the cascade classifier is shown in Figure 2.

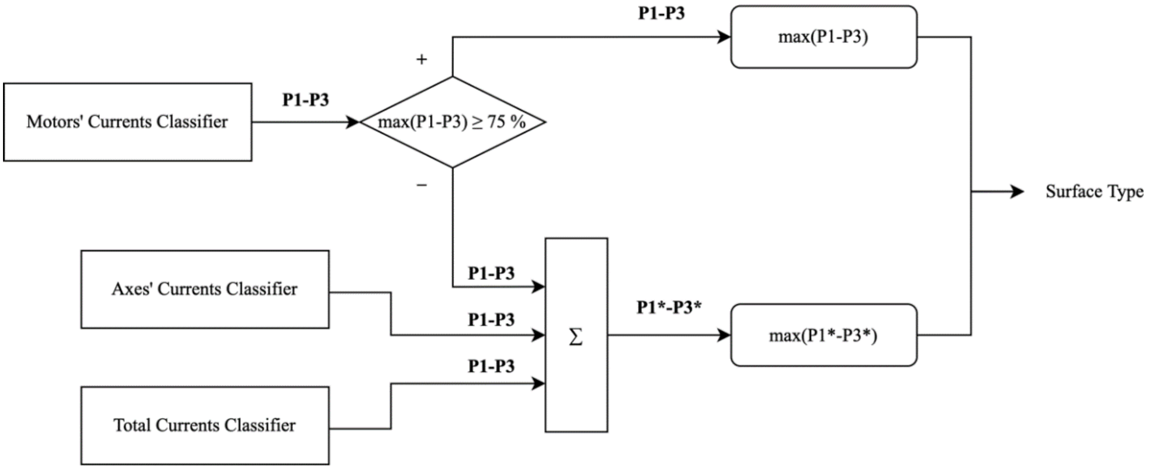

Fig. 2. Structure of the Cascade Classifier

Results

The cascade classifier and motors' currents classifier individually are checked on two data sets:

1. The set used for data analysis, dependencies extraction and further for classifier building;
2. The set gathered by a new method of motion vectors.

Accuracy is the ratio of the number of runs with the correct surface type detection to the total number of runs. Classifications results are shown in Table 1.

Table 1

Classification results

	Cascade Classifier		Motors' Currents Classifier	
Data Set	No. 1	No. 2	No. 1	No. 2
Accuracy	81.26 %	74.06 %	81.04 %	73.46 %

Conclusion

In this paper, a cascade of fuzzy classifiers was synthesized using the parameters of motors' consumption currents, currents along the axes and total currents of the mobile platform. The cascade classifier outperformed simple motors' currents classifier by about 0.4 %. Most likely, such insignificant increase in accuracy related to a small number of direct measurements in training data set.

Probably, overall accuracy falls in case of data set No. 2 for both cascade classifier and motors' currents classifier because of a new approach for data gathering. The set No. 2 contains more motion vectors than the set No.1 and do not include rotational component.

In the future, robot's technical equipment has to be expanded with additional sensors and a larger range of input signals of classifier should be researched.

References

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