Neural networks approach for odometers error estimation of mobile robot.

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Abstract

This article considers the approach of using of a neural network to estimate the odometry error in the mobile robot localization based on the odometers. As the odometers were used inexpensive optical odometers with a resolution of 48 counts per wheel revolution. Data obtained from the odometer using for calculating the position of the robot by means of a mathematical model of its differential kinematic schemes. Odometers data are also used for training the neural network. For training the neural network was used the trajectory of the robot as the reference data, obtained through chart pattern recognition system is mounted on the robot.

1. Introduction

One of the most important problems in robotics is determination the accuracy location of the robot - the problem of localization. This issue is important because information about the exact location of the robot is required to navigate, build path, etc. Today, there are several different approaches to solve the problem of localization. These approaches are presented in [1], [2], [3], [4], [5]. The most common approach to autonomous robot positioning in the room is SLAM [2]. However, for its implementation is required a robot equipped with laser scanner and a powerful processor. It is also possible failures in the case of positioning the robot in a dynamic environment.

The main object of the studies described in this paper is to improve the accuracy of positioning systems of real mobile robot based on using of the methods of artificial neural networks [6]. Positioning of a robot based on the odometer - the cheapest and, thus, a common solution in robotics. However, the using of odometers for positioning the robot in space is related to the problem of rapidly accumulating error caused by different factors. In detail the problem of odometer error is presented in [6]. In this paper, to improve the accuracy of odometers is proposed to apply the methodology of artificial neural networks to predict the accumulated odometer errors.

1.1 Specification of the robot

In the experiments has been used a two-wheeled mobile robot, equipped with odometers on each wheel, two infrared distance measured sensors, Wi-Fi communication module. The robot is shown in Figure 1. Robot has differential kinematics with two ball support wheels. As the odometer are used optical encoders with a resolution of 48 counts per wheel revolution. The size of the wheelbase of 8.825 cm for the experiments used infrared sensors distances Sharp with a range of 10-80 cm.

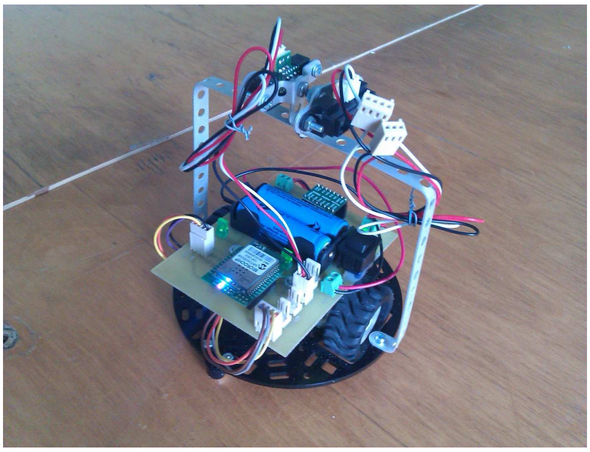


Figure 1 - Image of a mobile robot for experiments.

1.2 Odometry error model

The calculation of the current position of the robot used a mathematical model, was described below. Let the initial and final positions of the robot are given by the vectors:

$$P_0 = \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \end{bmatrix} \qquad P_1 = \begin{bmatrix} x_1 \\ y_1 \\ \theta_1 \end{bmatrix} \tag{1}$$

Odometers can get the instantaneous velocity v_l, v_r of the left and right wheels. If you know the size of the robot's wheel base b, the relationship between the initial, final coordinates of the position of the robot and the odometer data is follows:

$$P_1 = \begin{bmatrix} x_1 \\ y_1 \\ \theta_1 \end{bmatrix} = \begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \end{bmatrix} + \begin{bmatrix} \frac{v_l + v_r}{2} \cos\left(\theta + \frac{v_l - v_r}{2b}\right) \\ \frac{v_l + v_r}{2} \sin\left(\theta + \frac{v_l - v_r}{2b}\right) \\ \frac{v_l - v_r}{b} \end{bmatrix} \tag{2}$$

This dependence can be represented by the distance traveled and the total angle $\delta_{trans}, \delta_{rot}$ (Figure 2).

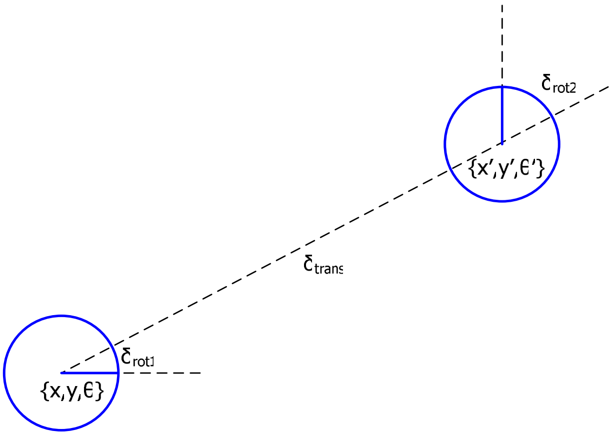


Figure 2 - The geometric model of the robot.

The expressions for the distance traveled and the rotation are follows:

$$\delta_{rot} = \frac{v_l - v_r}{b}$$
$$\delta_{trans} = \frac{v_l + v_r}{2} \tag{3}$$

Thus, the position of the robot calculated according to the next expression

$$\delta = (\delta_{rot}, \delta_{trans})$$

The error accumulated by odometers has two main components: systematic and random error. The reasons causing the systematic error are defects in the assembly mechanics and inaccuracy of designing components. Random errors caused by slippage of the wheels and uneven floors. Based on this calculation the resulting position and angle of the robot will contain these errors:

$$\hat{\delta}_{trans} = \delta_{trans} + \sigma_{trans}|d| + \varepsilon_{trans} \tag{4}$$

$$\hat{\delta}_{rot} = \delta_{rot} + \sigma_{rot}|d| + \varepsilon_{rot} \tag{5}$$

where $\sigma_{trans}, \sigma_{rot}$ systematic errors in estimating the distance traveled and angle of the robot, with a growing number of traversed distance $|d|$. ε_{trans} and ε_{rot} random errors in the distance and angle. $\hat{\delta}_{rot}, \hat{\delta}_{trans}$ actual distance traveled and the actual rotation angle.

1.3 Computer vision system for detecting the trajectory of the robot

To obtain the trajectory of motion of mobile robot was developed computer vision system. This system using for recognizing a graphical pattern, mounted on top of the robot. Applied for recognition webcam mounted on the ceiling over an area of the floor on which the experiments were performed to assess the position of the robot.

As the pattern used by a black square on a white background, centered on a black circle drawn in Figure 3. Pattern recognition is based on the detection, the image contrast of rectangles and check the black circle in the center.

Figure 3 - Graphical pattern for recognition.

Detection of the rectangles is in the shaping of images using Canny algorithm with subsequent approximation points of the contour lines. The contour is a rectangle if the following conditions: loop consists of 4 lines and the sine of the angle between the lines does not exceed 0.3.

In the interior of the rectangle allocated a path. The resulting points of the contour must defend at the same distance from the center of rectangle geometric mass, in this case, the contour will be a circle.

To improve the accuracy of the system used camera calibration to estimate the radial and tangential lens distortion. These coefficients are obtained by means of distortion image chessboard [7].

$$x' = x(1+k_1r^2+k_2r^4)+2p_1xy+p_2(r^2+2x^2)$$
$$y' = y(1+k_1r^2+k_2r^4)+p_1(r^2+2y^2)+2p_2xy$$

,where $r^2 = x^2 + y^2$, k_1, k_2 are radial distortion coefficients, p_1, p_2 are tangential distortion coefficients, $x' y'$ are undistorted image coordinates of point, xy are image coordinates of point.

The coordinate positions of the robot, resulting in recognition of the pattern, was treated to remove the perspective effect in accordance with the following formula:

$$x_r = x' + l\left|ox - x'\right|$$
$$y_r = y' + l\left|oy - y'\right|$$

where l are coefficient of perspective distortion, ox, oy are center of the image.

Recognition result is shown in Figure 7b.

1.4 Description of neural network

To estimate the increasing error is encouraged to use artificial neural network, which will predict the change in error over time. Since the odometer error depends on a variety of random and systematic factors, the change of error is a nonlinear dynamical system.

To predict the behavior of such systems and the subsequent correction of the position of the robot was used neural network with one hidden layer, which was used for training error back-propagation. The input layer of neural network consists of 10 neural elements, a hidden layer of 13, an output layer contains 2 neurons. The architecture of the neural network shown in Figure 4.

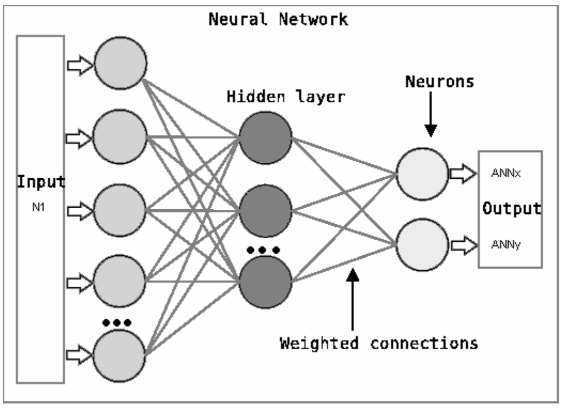


Figure 4 - The architecture of the neural network

For training the neural network was used the following approach. The input to the neural network serves odometer data and the start and end of motion. The input images have a follow form:

$$In = \{ x1, y1, x2, y2 \ldots, x8, y8, Ts, Te\}$$

Output neurons of a neural network formed by the values of the robot in the form of coordinates and ANNx ANNy respectively. For training the neural network as the reference values used the real position coordinates of the robot. The real position of the robot is estimated using two approaches - video recognizing of a robot with a camera mounted on the ceiling, and the data of infrared range finders.

Neural network training consist in reducing of the mean-square error E between the coordinate values obtained at the output of the network and coordinates obtained from measurements of the mobile robot with a camera:

$$E = \sum_n |ANNx,y - SENSORx,y|^2$$

The architecture of the neural network was chosen empirically to obtain a preliminary assessment of the quality of forecasting error.

2. Statement of the experiments

Traditionally, for researching the odometer error method is used UMBMark, proposed in [5]. At this stage of research experiments were conducted in a simplified form, as at the same time was carried out refinement of mechanical robot. The robot moved in a straight line along the wall at a constant speed 0.4 m/s specified amount of time. The experiments consisted in the fact that the robot was mounted on the starting position, then send the command to start the movement. When moving the robot odometer reading was carried out at intervals of 200 ms. 8 intermediate positions of the robot was calculated with the obtained data. From this information were formed the input pattern to the neural network.

For the formation of etalon pattern required for training the neural network was used points of trajectories which obtained from system for robot recognition.

For initial calibration of the robot reference position values were recorded using infrared rangefinders, perpendicular to one by another. In the process of calibrating the robot was moving along the wall, thus, indications of the rangefinders correspond to coordinates X, Y position of a real robot.

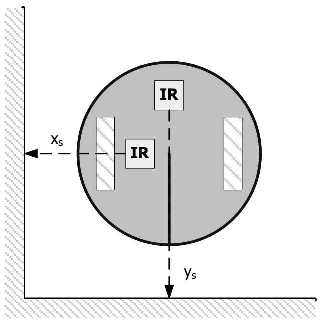


Figure 5 - Scheme for measuring the position of the robot with a rangefinder.

3 Experimental results

In the first phase of experiments was carried out the research of the characteristics of mobile robot mechanics. As a result, were received characteristics of behavior of the robot's mechanics in different conditions: a) straight-line motion on its own engines, b) the straight-line motion when the engine is in tow. Thus in Figure 6 shows plots of oscillation of instantaneous velocities of two wheels in the above described experiments. It is clear that the velocity fluctuations are present both wheels in motion mode on its own engines and towing mode. In addition, in the error are added the surface roughnesses. All experiments were performed on a surface covered with a special material to minimize the random component of error. Cameras and infrared sensors were calibrated with the object of reducing the error. Data from the infrared range finders were refined by the least squares method.

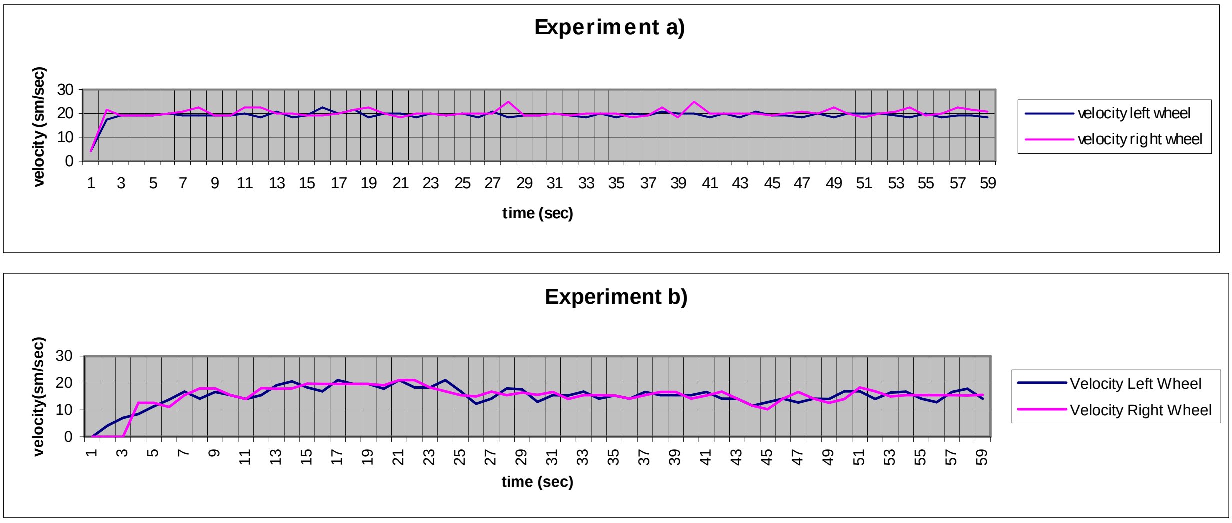
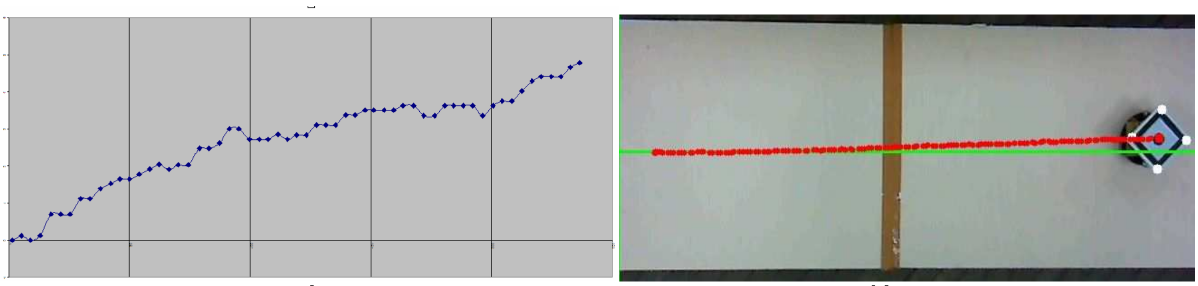


Figure 6 - Fluctuations in the velocity of wheels in the experiments a, b.

After setting up the equipment and calibration there were realized experiments for obtaining a training sample. A fragment of a training sample is shown in Figure 7. In the Figure 8a is represented the way of the robot, which is formed on the basis of odometers. In the Figure 8b is represented the path of the robot, which has been fixed with the video detector. It is clear that in time the error increases and odometers data begin to differ considerably. Fluctuations are clearly visible within the course angle of 4 degrees, that was caused by the small dimensions of the robot, namely a small wheelbase. Then is shown the effectiveness of the neural network for dynamic specification of the error and correction of the current robot's position.

time	Left encoder	Right encoder	IR range finder	Angle	Y coordinate	X coordinate
671029	0	0	192	1,827505	0,121164	3,797431
671430	5	5	129	-1,82751	-0,13014	4,078722
671633	18	19	167	0	0	3,940081
671838	33	33	163	1,827505	0,121164	3,797431
672044	47	47	163	1,827505	0,157064	4,922596
672243	60	61	169	3,656873	0,269253	4,21292
672478	77	79	164	1,827505	0,121164	3,797431
672677	91	95	157	-1,82751	-0,13911	4,360014
672877	104	109	164	1,827505	0,130139	4,078722
673077	120	124	165	0	0	3,940081
673277	134	139	165	1,827505	0,121164	3,797431
673477	148	153	165	0	0	3,940081
673677	161	167	165	3,656873	0,269253	4,21292
673878	175	181	165	1,827505	0,130139	4,078722
674078	189	197	165	0	0	3,940081
674284	203	212	164	0	0	3,940081
674483	217	226	171	3,656873	0,269253	4,21292
674689	231	240	171	0	0	3,940081
674889	245	256	171	5,489983	0,417342	4,342222

Figure 7 - Detail of the training set.



a) b)

Figure 8 - a) the path of the robot based on the odometer, and b) the actual path the robot

During the experiments, data of the position error in time were obtained. The resulting graph is shown in Figure 9. The graph shows that at the initial time interval of 1.6 seconds to sharp jumps in error, this situation is caused by the uneven inclusion of each of the engines, which leads to an error in addition to various factors such as race and interference power in the food chain odometers, a strong slipping wheels while turning the engine, etc. After stabilization of the engines, leveling of odometers vibration errors within the constant value takes place. Constant component provides by a systematic error, which is added regularly to the values of the position. Fluctuations are provided by the random component of error. Because of using special surface the random component is less than 1 cm.

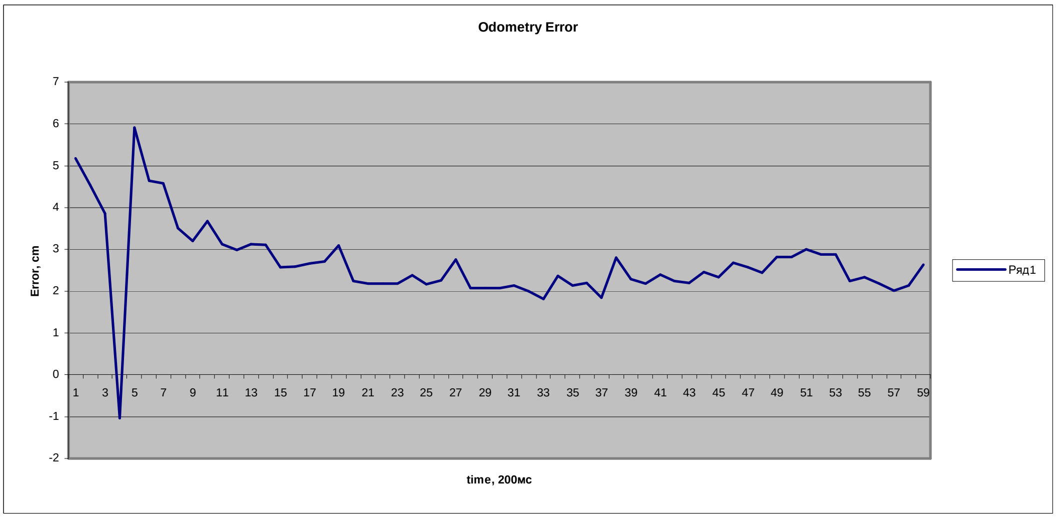


Figure 9 - The schedule change odometer error over time.

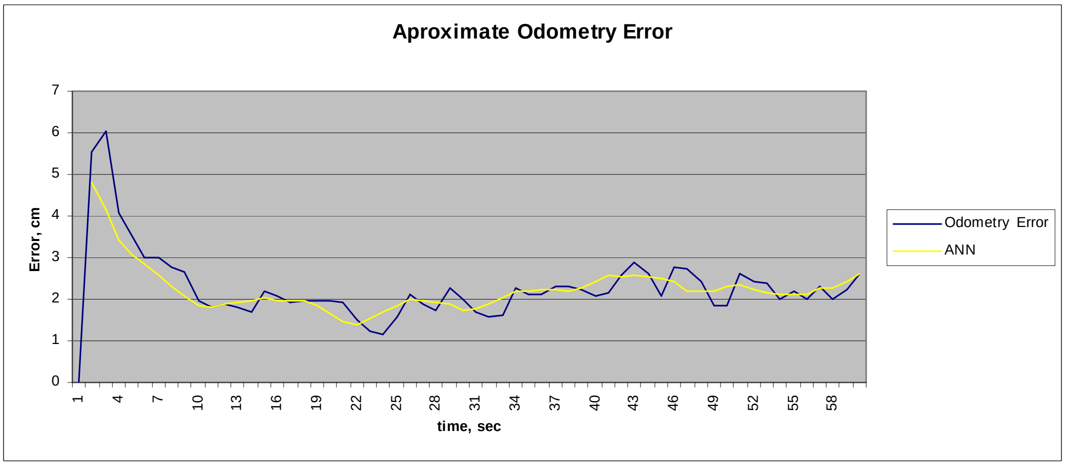


Figure 10 - Approximation errors odometers neural network

The neural network that was describe above has been used for prediction of this graph. After training the neural network there were obtained results that are presented in Figure 10. In the process of forecasting errors odometer changes to the architecture of the neural network was obtained the probability of 84%. This is because the prediction of the random component is difficult and requires an analysis of each situation. In represented results the neural network successfully predicted a systematic component.

Conclusions and Future Work

The research characteristics were obtained for the specific mechanics of a real robot. Based on these characteristics, was realized calibration of control subsystems and positioning of the robot to solve the problem of localization. To clarify the position of the robot and increasing the quality and reliability of the information provided by the localization subsystem has been proposed neural network module. Experimental results proved the success of the approach. However, this approach has several disadvantages, such as the need to configure the neural network module for the particular robot and environment, the demand for performance avionics robot, necessity of an external video camera to measure the actual position of the robot. In the future for solving these problems is planned to create the intellectual positioning system that could adapt during the operation to the parameters of the robot, the environment and used to estimate the position other sensors of the robot.

Acknowledgments

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