PRE-PROCESSING OF THE SENSORS INFORMATION FOR ROBUSTNESS CONTROL OF THE MOBILE ROBOT

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ABSTRACT

The neural system for orientation of the robot on unfamiliar district in this article is considered. In basis it lays several of the neural networks, which are united in the uniform system. The primal problem of the system is, that with an inexact information from sensor devices should to supply correct control of the robot.

1. INTRODUCTION

Now researches in the field of an artificial intelligence based on the neural network theory. In their basis lays the neural organization of the artificial system lays, which has the biological premises. The ability of biological system to training, self-organizing and adaptation has large advantages before the computer systems. The advantages of computer systems are the large speed of distribution of the information and the possibility of the stocktaking of large volume of knowledge of saved by humanity in various areas. Development of artificial systems, which connects advantages of biological essences with modern computer engineering, creates the preconditions for conversion of evolution in computer engineering to a new qualitative stage.

In this work described the intellectual neural system for autonomous control of the mobile robot. As sensor inputs, providing the source information for such a control system we will consider: diagram of the environment conditions from sensor devices; dead responding based on wheel encoders (coordinate of initial and final point of robot movement is given). As touch devices the inexpensive ultrasonic sensors and infrared scanner are used. The information of multiple inexpensive sensors will be combined by data fusion and adaptive control schemes to derive a fault tolerant, robust performance of robot. In particular when inexpensive sensors will be combined by intelligent algorithms to derive efficient reactions, there can be expected an interesting economic of potential. Due to the current technical basics the "value money", e.g. The rating investment versus potential scientific/industrial benefits seems particularly good. On the basis of the information from sensor devices, the neural network should generate the direction and speed of movement. As basis of such a control system, we want to use the various neural nets for the different functionality's, which are to be combined in an intelligent system. In a common case the neural system decides the following tasks:

- Sensor data fusion
- Construction two-dimensional occupancy grids using sonar sensor and infrared scanner
- Obstacle detection and definition an optimal movement range
- Direction finding of movement in a selected range.

2. ARCHITECTURE OF A NEURAL SYSTEM

The common architecture of a neural system for autonomous control of the robot is fig.1. The system consists of various types of neural networks.

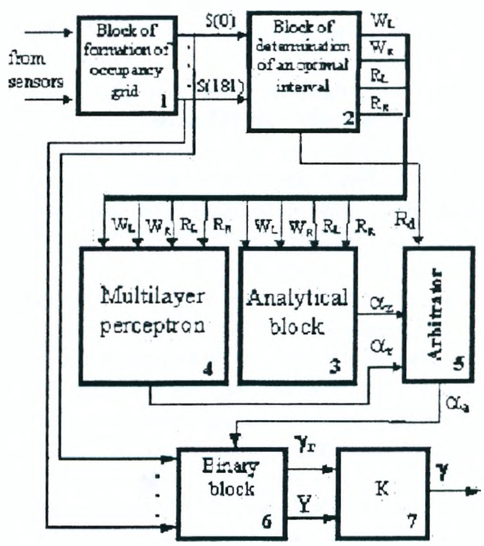

Fig. 1. Neural system for autonomous control of the mobile robot

In a figure the main links and blocks of the system are shown only. Sensors location has shown in fig.2. The block of formation of an occupancy grid creates (source of the information the sensors are, they have the following parameters: radius of the browse of 2.4 meters, angular range 180°) map of linear and angular distances up to obstacles S (i), $i = \overline{1,181}$. S – distance up to an obstacle in a direction of an angle i. Besides the block generates an oblate occupancy grid S(p), $p = \overline{1,36}$, which is used for control of the binary block.

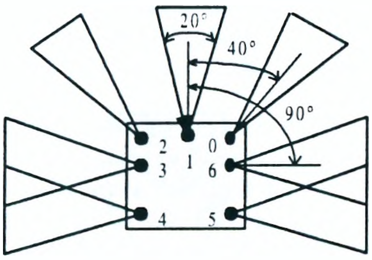

Fig. 2. Ultrasonic sensors configuration

The block of determination of an optimal interval of driving is intended for selection in enclosing space of a free interval of driving. The free interval is characterized by that it is most close to the final point. The information on an output of the given block corresponds linear (R_L, R_R) and angular (W_L, W_R) to distances of the selected interval of driving (fig. 3).

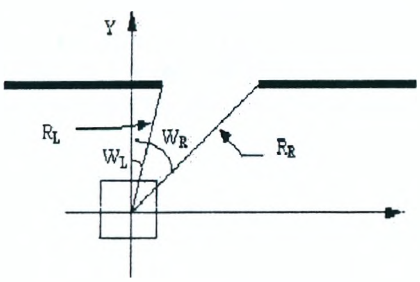

Fig. 3.The used characteristics of an interval of driving

If not the free interval of driving is selected, there is a turn of the robot on 90°, and search of a free interval. Also can driving the robot back for an exit from lockup is carried out. The analytical block is intended for definition of an optimal direction α_t in a selected interval of driving. The optimal direction is characterized by such direction of driving, which provides minimum angular distance up to the target. The analytical block controls driving of the robot on the large intervals of driving, when R_d>2d. Here R_d – width of the selected interval of driving, and d– width of the robot. Structure and algorithm of operation of the considered above blocks explicitly are circumscribed in [1-6].

The multilayer perceptron is intended for orientation of the robot on narrow intervals of driving, where R_d < 2d. It forms a robust direction of driving of the robot – α_r. On narrow intervals of driving the inexact occupancy grid becomes interference for orientation of the robot. If to train a multilayer perceptron to correct output data at the inexact input information, at the expense of generalizing ability it will provide robust control of the robot.

The arbiter depending on a situation forms a current direction of the robot:

$$\alpha_a = \begin{cases} \alpha_t, & if\ Rd > 2d \\ \alpha_r, & otherwise \end{cases} \qquad (1)$$

The binary block is for control of the robot in a situation, when side distance up to an obstacle $\Delta \le \Delta m$ is too small for realization of turns. The given block will transform the input information to the binary array. The direction, which forms the binary block, does not exceed 1°. It provides exception of contact of the robot with side obstacles. The commutator depending on a situation forms a final direction of driving of the robot:

$$g = \begin{cases} \alpha_a, & if\ Y = 0 \\ g_r, & otherwise \end{cases} \qquad (2)$$

where Y=1, if $\Delta \le \Delta m$.

Thus depending on a situation the robot can be controlled by the following units:

- The analytical block
- Multilayer perceptron
- The binary block together with analytical
- The binary block together with a multilayer perceptron

Such approach provides steady driving of the robot in various situations. The neural system uses the system of the near and long-distance browse. Speed and step of driving of the robot are normalized depending on distance up to an obstacle. The break of the robot happens, if distance up to the purpose is less than the defined value ε.

3. MULTILAYER PERCEPTRON

The multilayer perceptron is intended for orientation of the robot on narrow intervals of

driving. It provides steady control of the robot at the inexact information from an occupancy grid and forms a robust direction of driving α_r. The architecture of the given block shown in the fig. 4.
The block MLP consists of four entry, six hidden and one output unit.

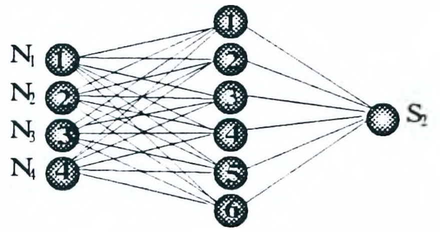

Fig. 4. Structure of the block MLP

As the entry information are used linear (R_L, R_R) and angular (W_L, W_R) distance up to obstacles (fig. 4), which are scaled according to the following expressions:

$$N_1=R_L/600, \quad (3)$$
$$N_2=R_R/600, \quad (4)$$
$$N_3=(W_L/100+1)/2, \quad (5)$$
$$N_4=(W_R/100+1)/2. \quad (6)$$

The information on an output of a neural network MLP characterizes a direction of driving of the robot α_b, which is defined as follows:

$$\alpha_r = \text{int}(2S_2-1)100, \quad (7)$$

where S_2 –output value of a neural network.
The creation of learning sampling is made for the block MLP as follows. Changing in scopes of an obstacle a position of the robot and turns with selected step of a discretization concerning a current position. Thus we obtain a collection of training sets.
In case of the inexact information the real position of an obstacle can differ from an occupancy grid that sees the robot. Such situation is shown on fig 5, where the solid lines represent a position of an obstacle, which sees the robot, and dashed – real position of an obstacle.

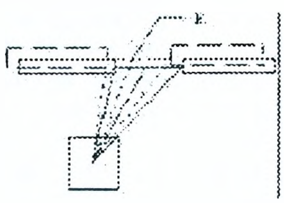

Fig. 5. Possible distirtion of a visible interval of driving

For support of robust control of the robot at an inexact occupancy grid it is necessary in appropriate way to select a position of point K from the selected interval of driving (fig. 5). If to train a neural network to correct output data, it can provide steady control of the robot at an inexact occupancy grid. The concept of training of a neural network MLP generally consists of the following steps:

- Operator controls the robot, simulating passing of various intervals of driving.
- For each interval of driving the point K, describing a real position of the robot in this interval and characteristic of an interval (W_L, W_R, R_L, R_R) is defined at various positions of the robot.
- Rotations input and output data in range 180°, are formed learning patterns.
- Training a neural network MLP by a method back propagation is made.

The given algorithm is characterized by a minimum set of the experimental data. It is enough to define only position of a point To and characteristic of an interval of driving. The computer simulation of a multilayer perceptron is carried out. Size of learning sampling for the block MLP –60 sets.
Time of training of a neural network MLP has made on the average 10^4 iterations at a summarized mean square error $5*10^{-3}$. After training the robot successfully passed from various positions through narrow apertures, successfully bent obstacles, despite of the screwed entry information. In outcome the robust control of the robot is provided at a uncertain occupancy grid.

4. BINARY BLOCK

The disadvantage of the previous blocks of direction finding of driving is, that they do not take into account distance from the side sides of the robot up to an obstacle. In outcome at realization the robot of manoeuvres can happen collision to obstacles.

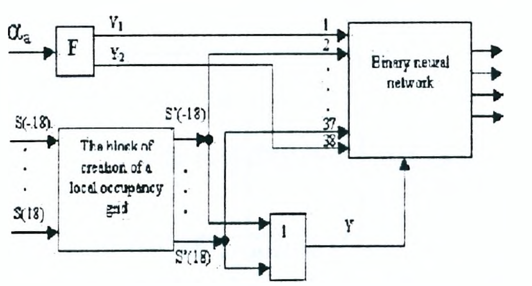

Fig. 6. The binary block scheme

To maneuver without collisions it is necessary, that side distance up to an obstacle was more than radius of the circle, circumscribed around of the robot:

$$S > \frac{d}{2}\sqrt{2}, \qquad (9)$$

where d –width of the robot.

If the condition (9) is not fulfilled, the control of the robot makes the binary block. In this case corner of turn of the robot in this or that direction is a constant and is equal to one degree.

The binary block scheme for creation of a direction of driving is shown in the fig. 6.

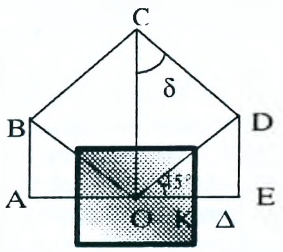

Fig. 7. Configurations of a local occupancy grid

The block F is intended for conversion of an angular direction of driving α_i in binary sort. It is necessary for control of a binary neural network. The block F is intended for the following functions:

$$Y_1 = \begin{cases} 1, & if\ a_a > 0 \\ 0, & otherwise \end{cases} \qquad (10)$$

$$Y_2 = \begin{cases} 1, & if\ a_a < 0 \\ 0, & otherwise \end{cases} \qquad (11)$$

The block of creation of a local occupancy grid is intended for obtaining an occupancy grid of the given configuration (fig. 6) and generation of a signal Y of activation of a binary neural network.

Such card is necessary for exact control of the robot in situations, when an obstacle to be too close (on distance less Δ) with a side of the robot (fig. 7). The triangular form is selected outgoing from support of smooth manoeuvres at presence of obstacles on front of the robot. As the input information the block of conversion uses an oblate occupancy grid consisting of 36 units. The technology of conversion is, that if an obstacle to be in a zone ABCDE, the appropriate units S' (p) are installed in single values, otherwise in zero values (fig. 8)

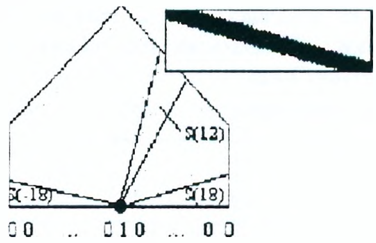

Fig. 8. Example of the local occupancy grid creation.

In outcome the binary array turns out which characterizes presence in the given area of obstacles. The block of conversion consists of one stratum of threshold neurons (fig. 9), each of which corresponds to the defined sector of an occupancy grid.

The neurons are intended for the following functions:

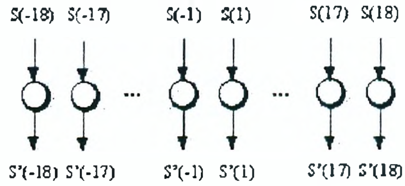

Fig. 9. Creation of a local occupancy grid

$$S'(p) = \begin{cases} 1, & if\ S(p) \le T(p) \\ 0, & otherwise \end{cases} \qquad (12)$$

Here T (p) – threshold of the given neuron. For creation of the binary array in the given area it is necessary in appropriate way to form threshold values of neurons.

The binary neural network is intended for control of the robot, when the turns on the large values can reduce in collision with an obstacle. In this case Y=1 (fig. 6). Such network represents three-layer feed forward neural network (fig. 10).

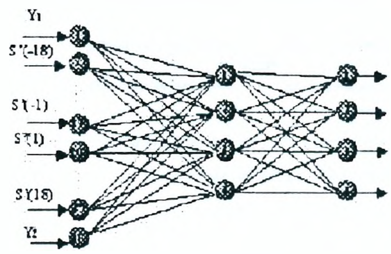

Fig. 10. Binary neural network

As the function of activation of units the sigmoid is used. On an output of a neural network the commands of control of the robot (fig. 11) are formed.

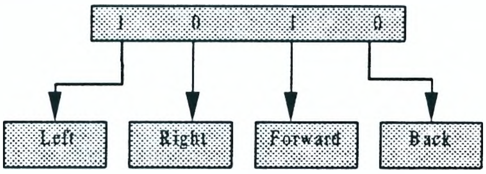

Fig. 11. Control commands of the robot

Thus the turn in the defined instant happens on 1°, that eliminates collision of the robot with side obstacles. For control of the binary network the signals Y_1 and Y_2 are used also which turn out by conversion of a direction of driving α_t from the block 5 (fig. 1). So, if $Y_1=1$, that corresponds $\alpha_t>0$, the binary network will form the command of turn to the right on the value 1°. Such interaction of blocks 3,4 and 5 provides driving the robot in the nearest direction to the purpose. Especially actual it is at existence of the alternate paths of driving in narrow mazes (fig. 12).

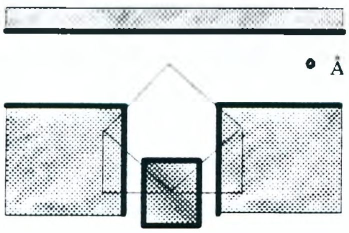

Fig. 12. Drivings of the robot in a maze under the control of the binary block: E –target

The binary network works by a principle of overcoming of an obstacle. The possible variants of its operation are represented in a fig. 13

Fig. 13 Creations of commands of control with the help by a binary neural network

In the second variant the turn happens until then there will be no yet overcoming of an obstacle.
For training the binary network it is necessary to generate training sets. The generation of learning sampling is characterized by a simplicity and implies from logic of operation of the given network. In table 1 the training sets for some situations are reduced.

Table 1

Input pattern	Output pattern
0110000000000000000000000000000000000001	1010
1000000000000000000000000000000000000000	0110
0000000000000000000000000111111111111110	1000
0011111110000000000000000000000001111100	0010
0000000000000000000000000000000000000000	0010
0111111111111111111111111111111111111110	0001

For training the binary network the algorithm back propagation was used. The size of learning sampling has made 30 sets. Duration of training – $3*10^3$ iterations, total mean square error $-1*10^{-3}$. Alongside with the logical approach to creation of learning sampling the algorithm can be applied which the operator at hand-held control of the robot bases on simulation of various situations. It provides creation of a correct direction of driving at an inexact occupancy grid.

5. EXPERIMENTS OUTCOMES

Software for simulation of the robot movement is developed for the neural system testing. The learning and simulation was conducted for want of inexact information from an occupancy grid. It results that the sizes of a real obstacle differ from the sizes, which sees the robot. However learning on correct output data will neutralize this disadvantage. At the expense of it is ensured robust movement of the robot.

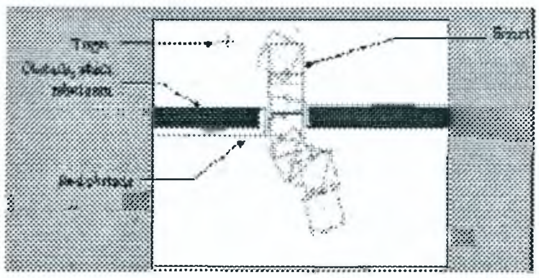

Fig. 14. Robot movement to the target with inexact information from sensor devices

The testing of the system was conducted for various types of obstacles and has shown stable operation of the robot (Fig. 14).

6. CONCLUSION

In this work operation neural networks for autonomous control of the robot on narrow intervals of movement are described. It characterized by that with appropriate learning is capable to ensure correct control of the robot with an inexact information from sensor devices. The neural networks computer simulation is conducted, which has shown stable operation them for control of the mobile robot. Real experiments are planned to realize on the really operating robot "Walter" (GERMANY).

7. ACKNOWLEDGEMENT

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