The Local Area Map Building for Mobile Robot Navigation Using Ultrasound and Infrared Sensors

Keywords: mobile robot, local area map of mobile robot, artificial neural network, training set of neural network, sensor fusion, sensor data processing.

1. Abstract

This paper was devoted to improvement of existing and development of the new method for local area map building of mobile robot using sensor fusion techniques. Such task is arisen from unstructured environment for navigation of mobile robots. The offered method provides building of the local area map using polar coordinate system and bases on the applications of artificial neural network for fusing of readings from ultrasonic and infrared sensors. Application of the proposed method allows to decrease computational complexity and to increase the accuracy of local area map.

2. INTRODUCTION

Autonomous mobile robots (AMR) as universal technical systems, which allow independently execute the mechanical actions, are one of the most modern directions of scientific researches [1, 2, 3]. AMR, that has intelligent facilities, applies in many industries, oriented both to the indoor environments, created by a human, and outdoor unstructured environments, for ground, air, space and submarine applications [1, 4, 5]. Especially actual are the applications of AMR in the aggressive unstructured environments where the presence of human is impossible or harmful, for example after catastrophes, fires or assassinations. One of the problems, which arise up for the navigation of AMR in the difficult unstructured environments, consists in determination of positions of obstacles that prior are unknown. In addition, presences of the dynamical objects in the environment provide difficulties with using of the pre-programmed robots. Such conditions of AMR functioning lead to the origin task of necessity in local area map building (LAM) as part of the robot autonomy, decision-making and adaptation to the unknown environments [4]. Thus, a construction of LAM is the important and fundamental task of functioning of AMR.

3. EXISTING APPROACH FOR LOCAL AREA MAP BUILDING FOR MOBILE ROBOTS

In order to provide the effective analysis of input data and build LAM by AMR, it is necessary to have a powerful model of sensors. For this reason the existing approaches of obstacles detection for AMR divide on two categories: active and passive perception [6]. The passive perception approaches are based on matrix processing of the data obtained from the preliminary lighted or marked areas of the environment, when the active perception approaches provide analyses of a delay in distribution of signal from the beginning of his generation to the moment of its reflection from obstacles. At the general cases, the methods of passive perception contain more useful information about the environment and at the same time greater computational complexity than methods of active perception [7]. Taking into account the necessity of functioning of AMR in the real time, at this paper we will consider the methods of environment modeling by AMR using active perception as fusion of infrared scanner (IS) and ultrasonic sensors (US). At the present time there are a lot of implementations for modeling of LAM, basing on the fusion of US and IS [8, 9, 10, 11, 12]. Let consider the basic approach for modeling of the environment, basing on German AMR „Walter” [12]. On the platform of mobile robot “Walter” there are seven US and one IS. US are placed on the perimeter of AMR (fig. 1a) and are characterized by frequency of signal transmitting in 45 Hz. The range of linear distance detection to the obstacle is 10 meters and the corner of obstacle detection is 20°. As a result, using of US allows precisely to measure linear distance to obstacle, but it is not enable precisely to define angular data to the obstacle [12, 13, 14]. At the same time the linear distance detection for IS is at the range from 0.3 to 2 meters. IS divides the scanned angle of 180° into 36 sectors (fig. 1b). The angular range of one sector is 5°. As a result, the error of evaluating of linear distance to obstacle by using of IS is higher than the error of US.

![Fig. 1. Position of US (a) and IS (b) of mobile robot “Walter”](image)

The algorithm of LAM building consists in the fusion of US and IS readings in order to precise the linear and angular measuring distances to the detected obstacles. Thus fusion of sensors values is carried out by a geometrical
method with corrections of US values by IS values. Complication of algorithm consists in execution of three basic stages (the first stage contains four steps, the second and the third steps contain two steps each) [12]. After execution of the basic stages of the algorithm, the LAM is created in polar coordinate system as the distance to the obstacles in 36 directions relatively to AMR. Linear interpolation is executed for the evaluating of more detailed LAM in a range from 0 to 180° and need additional three steps of the algorithm (fig. 2).

![Fig. 2. Local area map of AMR:](image)

a) input data from US (1) and IS (2); b) local area map in polar coordinate system

Thus, in general cases, the existing method of LAM building is characterized by the complications of realization, by hardware inflexibility (for each sensor position it is used own procedures and approach for LAM building), hard dependability of the developed software to the robot hardware (in the case if the hardware and sensor positions were changed it would be impossible to correctly adapt the existed software), ineffectiveness of using readings from IS in the range of sectors -18 and 18, low precise of evaluating of distance to obstacle taking into account linear approach and interpolation of LAM.

4. THE NEW APPROACH FOR LOCAL AREA MAP BUILDING FOR MOBILE ROBOT NAVIGATION USING ULTRASOUND AND INFRARED SENSORS

As shown higher, the development of the intelligent control system that is able to provide self-modeling of the environment is the actual task for AMR autonomy [15, 16]. The existed statistical method has disadvantages and it has not intelligent properties for estimating of the obstacle positions in the environment that may provide an inadequate reaction of AMR in the case of mistake readings from the sensors. That is why the new neural based method was suggested for LAM building. This method is based on the using of neural networks (NN) and readings form IS and US for evaluating of positions of obstacles in the polar coordinate system [15].

Similarly to the existing method we are dividing the space that is scanned by IS and US into three types: spaces where ranges of US and IS are overlapped (fig. 3a), spaces where readings of US and IS are not overlapped (the parts of the environment that is located between two nearby US on fig. 3b), and spaces where it is impossible to provide fusion of readings of IS and US (fig. 3c). The new method consists in the building of LAM basing on the approximation of readings obtained from IS and US by two NN. First NN provides fusion of sensor readings at the first type of space. Second NN provides approximation of LAM in the second type of space.

The building of LAM in third kind of space is provided by linear interpolation of IS readings with the step in 1°:

$$MAP_i = IR_j, \quad i = 1..180, \quad j = 1..36,$$

where $MAP_i$ is a value of linear distances to the obstacles of LAM in accordance with an i-angles of polar coordinate system; $IR_j$ readings of j-sectors of IS.

![Fig. 3. The space of the environment scanned by IS and US (the dark areas represent the ranges of space scanned by US with the angle of 20°, light areas depict sectors of IS with angle of 5° each)](image)

The task of the first NN is to provide approximation of $q$ readings from US and IS in order to obtain Z values of LAM with the step in 1°, where Z is a segment of the environment that covers US. For this goal we are using the feed-forward NN as multi-layered perceptron with one hidden layer (fig. 4). Selecting of such NN was based on the wide applications of such kind of NN for the decision making, predictions and approximations [17-21].
The input layer of NN includes readings of such US and sectors of IS that are overlapped in his angle range. Thus NN contains \( R+1 \) of inputs (\( R \) is an amount of sectors of IS that overlaps with US), \( S1hid \) - neurons of intermediate layer that execute transformation of information given from an input layer and \( S2out \) - neurons of output layer that represent the value of distances to the obstacles of such area of LAM that cover a range of US with the step in \( 1^\circ \). Every layer of NN contains the matrix of weight coefficients of \( W \), vector of threshold values of \( b \) and vector of output values \( a \). Output of every layer of multi-layered perceptron founds as

\[
\begin{align*}
a_j^1 &= f^1 \left( \sum_{k=1}^{R+1} \left( w_{k,j} a_k^0 + b_j^1 \right) \right); \\
a_j^2 &= f^2 \left( \sum_{i=1}^{S1hid} \left( w_{i,j} a_i^1 + b_j^2 \right) \right).
\end{align*}
\]

where \( f1 \) and \( f2 \) are transfer functions according to the hidden and output layer of NN; \( w_{k,j} \) are weight coefficients of input layer from a \( k \)-input to the \( j \)-neuron of the hidden layer; \( w_{i,j} \) are weight coefficients of the hidden layer from \( I \)-neuron of the hidden layer to the \( j \)-neuron of output layer; \( a_k^0 \) is a \( k \)-input of NN; \( a_j^1 \) and \( a_j^2 \) are outputs of \( j \)-neurons of hidden and output layers; \( b_j^1 \) and \( b_j^2 \) are thresholds values of \( j \) neurons of hidden and initial layers; \( R+1 \) is a number of inputs of NN; \( S1hid \) is number of neurons of the hidden layer.

The nonlinear log-sigmoid transfer function is used for the neurons of the hidden layer

\[
f(x) = \frac{1}{1+e^{-x}},
\]

and the linear transfer function is used for the neurons of output layer

\[
f(x) = k * x,
\]

where \( k \) is a coefficient, which represents the angle of line of the graph of activating function.

Thus, the outputs of every intermediate layer of NN are inputs to the next layer. That is why the output of the second layer can be also analyzed as one-layer NN with \( S1hid \) inputs, \( S2out \) neurons and weighing matrix \( W2 = S2xS1 \). The inputs for the second layer of NN are \( a1 \) vector, and the outputs are \( a2 \) vector. The same approach is taken for any layer of NN.

It is possible to use procedure of simulation of first NN for LAM building in the interval of overlapping US and sectors of IS:

\[
MAP_{i=2}^{R+2}, MAP_{i=5}^{R+2} = NN1([IR_j, ..., IR_j, R, US_k]); i = 1,178; j = 1,36; k = 1,5; IR_j \in US_k,
\]

where \( MAP_{i=2}^{R+2}, MAP_{i=5}^{R+2} \) - values of distances to obstacles of LAM, which are generated by first neural network NN1; \( I \) - is a angle of the polar coordinate system of LAM; \( IR_j \) is a value of \( j \)-sectors of IS, which are given on the input of NN1; \( R \) is a number of sectors of IS, which intersect with US; \( US_k \) is a \( k \)-value of US, which is given on the input of NN1.
It is expedient to use the algorithm of Levenberg-Marquardt backpropagation [17] or Resilient backpropagation (RPROP) for training of NN [21]. These algorithms provide rapid achievement of mean-square error of training of NN. Also the first algorithm provides a rapid ascent to the desired precision of training of NN, however it needs more memory, unlike the second. The training set of NN consists the vector of training inputs and vector of training output. The inputs of NN are values of US and IS readings, and the vector of output is determined on the basis of the real distances to obstacle in the environment of AMR with the step of 1º.

In the case of sensors position, in which range of US is not overlapped with the sectors of IS and sectors of IS are between two ranges of nearby US (fig.3b), it is expected to use the second approximated NN. This kind of NN is used in order to construct LAM at the intervals between two nearby US. The structure of second feed-forward NN is in the form of multi-layered perceptron, which contains one a hidden layer and allows to evaluate approximation of information is used (fig. 5) [17, 19, 20].

The difference between the structure of second approximated NN and the structure of the first NN consists in the input layers. The input of the second NN consists of the readings of two nearby US and readings of such sectors of IS, which are located between ranges of US. Thus, approximating NN contains \( R+2 \) inputs, \( S_{1}^{\text{hid}} \) hidden neurons and \( S_{2}^{\text{out}} \) of output neurons. The output of NN is evaluated like (2.9).

![Figure 5. Structure of second NN for the construction of areas of LAM located between slopes of two nearby US](image)

It is used the procedure of simulation of second approximating NN for the construction of LAM in an interval between ranges of two nearby US:

\[
\overline{MAP_{i-2}, MAP_{i+5+R+2}} = NN2([IR_j, ..., IR_{j+R}, US_k, US_{k+1}]), i = 1,178, j = 1,36, k = 1,4,
\]

where \( MAP_{i-2}, MAP_{i+5+R+2} \) – distances to the obstacles of LAM, which are generated by approximated neural network NN2; \( i \) - is an angle of the polar coordinate system of LAM; \( IR_j \) - is a value of \( j \) sector of IS, which is inputted to neural network NN2; \( R \) is a number of sectors of IS, which are located between two nearby US; \( US_k \) is a \( k \)-readings of US, which is given on the input of neural network NN2.

It is expedient to use the algorithm of Levenberg-Marquardt backpropagation [17], that provide rapid achievement of mean-square error for training of second NN. As well as in in the first NN, the training set of inputs is formed on the basis of readings of US and IS, and the vector of output is determined on the basis of the real distances to the obstacles in the environment of AMR.

After the construction of LAM of AMR it is necessary to limit the radius of linear distance to obstacle of MAP(j) to the value which is set by the sensitiveness of sensors in relation to evaluating of linear distances to obstacles (for example for sensors of "Lauze of electronic" [12] threshold sensitiveness is equal to 2.4 m).

\[
\begin{align*}
MAP(i) &= MAP(i), & \text{if} & \quad MAP(i) < 2.4 \text{ m}, & i & = 1,180; \\
MAP(i) &= 2.4 \text{ m}, & \text{if} & \quad MAP(i) \geq 2.4 \text{ m}, & i & = 1,180.
\end{align*}
\]

Thus the construction of LAM by offered new neural-based method consists in four basic stages (fig. 6):

- construction of the areas of LAM, for which it is impossible to provide fusion of readings from US and IS;
- construction of the areas of LAM, in which the ranges of US and IS are overlapped;
- construction of LAM, for areas where ranges of sectors of IS are located between a ranges of two nearby US;
- limitation of linear distance of LAM by the value of sensitiveness of sensors and filtering of their values by a median filter.

In order to estimate the complexity of the offered method, let’s consider the algorithmic complication of it using the analytical approach above. Let use the sensor configuration depicted on fig. 3a for comparison of the algorithmic complication of the offered and existed methods.
Fig. 6. The flowgraph of the algorithm of LAM building by AMR using the offered neural-based method

The computational complexity of the offered method can be presented by the following formula:

\[
    \text{Calc} = \text{TrSET}(\text{NN1, NN2}) + \text{TRAIN}(\text{NN1}) + \text{TRAIN}(\text{NN2}) + \\
    + \text{SIM}(\text{NN1}) + \text{SIM}(\text{NN2}) + 180, \tag{2.10}
\]

where TrSET(NN1, NN2) – procedures of forming the training sets for first NN1 and second NN2 neural networks; TRAIN(NN1), TRAIN(NN2) – training procedures of first NN1 and second NN2 neural networks; SIM(NN1), SIM(NN2) – simulating procedures of NN.

Thus, if to assume that for the construction of LAM needs 100 training vectors, algorithmic complication of the offered method in accordance to (2.10) is equal to 100 creating of trainings sets for NN, 4 training and simulating procedures of NN, 180 limitations of radius of LAM that makes 284 operations totally. At the same time the algorithmic complication of the existed method include 492 analytical operations that are 208 operations more than in the offered algorithm. This fact demonstrate that offered method has less computational complexity and higher processing speed than existed method.
The offered method of LAM building was designed using Matlab 6.5 [22]. The model of the environment is presented in the form of binary matrix (fig. 7). In order to provide modeling of the environment we are considering the configuration of AMR, which contains 36 sectors of IS and 5 US with the angular orientation in 10°, is used, 50°, 90°, 130° and 160° (fig. 3a).

The modeling of the readings for each sectors of IS was provided with the angular error of 5° and maximum linear distance error to the obstacle in 30 cm (fig. 8a, 9a).

Fig. 7. The model of the environment for LAM building:
   a) binary matrix of the environment; b) environment parameters

Fig. 8. The training process of the first approximating neural network:
   a) training set of neural network; b) diagram of the training process of neural network;
   c) interpretation of training set by the trained neural network
The readings of every US were modeled with the angular error in 20° and maximal error in 10 cm relative to linear distance to the obstacles (fig. 8a). At that the errors on an arbitrary interval [a, b] are distributed with the normal law of distribution for each of the sensors:

\[ y = a + (b-a) \times \text{randn}, \]

where \( a \) - is the low boundary of the interval of measuring error; \( b \) - is upper boundary of interval of measuring error; \( \text{randn} \) - is a function of generation of random numbers, distributed with the normal law of distribution on an interval \([0, 1]\).

Next configurations of NN are considered with purpose of presentation of functioning of NN for the LAM building by AMR. The structure of the first NN contains 5 inputs, 15 neurons of the hidden layer with the sigmoid transfer function and 20 output neurons with the linear transfer function (fig. 4). Second NN contains 6 inputs, 15 neurons of the hidden layer and 20 output neurons (fig. 5). The number of neurons of output layer of each NN depends on the angular resolution ratio of sectors of IS. The training sets of each NN are formed from the readings of US and IS, which were modeled and contain noises, and also known linear distances to obstacles with the step of 1°. The algorithm of Levenberg-Marquardt, which is implemented in the environment of MATLAB 6.5, is used for training of NN [17, 22]. In addition, the experimental results show that it is necessary to limit the training of NNs (fig. 8b, 9b) to 100 epochs for avoiding of effect of their converting into associative memory. Every epoch is one iteration, in which training set (set of training vectors) that is given to the input of NN provides calculation of mean-square errors, new values of weighing coefficients and thresholds of NN. The approximation processes of training sets by NN are presented on fig. 8c, 9c. Training sets for NN were created basing on the sensor readings of AMR at 8 positions in the modelled environment (fig. 8a, 9a).

The example of area of environment, which was built with using of the first NN, is shown on fig. 10a. The abscise axis depict the part areas of the environment, for which readings of US and IS are overlapped. According to the selected configuration of AMR it is possible to select 5 areas of the environment where the readings of IS and US are overlapped. Every area of the environment contains 20 values of linear distances to the obstacles with the step of 1° of the polar coordinate system, which form the range of values of 20 x 5 = 100 points on LAM. Absolute deviations of the
built environment of AMR from real values are shown on fig. 10b. Mean-square error of LAM, which was built by the developed method, is equal to 13 centimeters, while a similar parameter of the existed method is equal to 19 centimeters, that in 1,5 times more precisely.

The example of area of environment, which was built by the second NN, is shown on fig. 11a. The abscise axis depict the built environment at the range between two nearby US. According to the used configuration of AMR it is possible to select 4 part areas of the environments, for which the values of IS and US are not overlapped. Every area of environment contains 20 values of distances to the obstacles of the environment with the step of 1° of the polar coordinate system, which form the range of values of 20 x 4 = 80 points of LAM. Absolute deviations from the real values of the built environment of AMR are shown on fig. 11b. Mean-square error of built LAM by the offered method is equal to 8 centimeters, while a similar parameter of the existed method is equal to 32 centimeters that in 4 times is more precisely.

In order to present the advantages of the offered method let consider the sensor readings of AMR that presented on fig. 12. In addition let specially change the readings of third US in order to provide the imitation of corruption for this sensor as a result of absorption of ultrasonic impulse by an obstacle or reflection of it in opposite from sensor direction.
At the fig. 13 it is presented the built LAM of AMR in the polar coordinate system by the offered and existed methods basing on the readings of US and IS (fig. 12). As a result the obstacle that is located at the front position from AMR is not detected by the existed methods because of inaccuracy of third US. However obstacle was successfully detected by neural-based method as a result of adaptation of NN to the presented conditions. The training set which contained 112 positions of AMR in the different areas of environment was used for reliable detection of the obstacle (training time of NN is equal to 9 epochs). Mean values of absolute deviations from real linear distances to the obstacles by the existed method are equal to 19 centimeters in the presented example and, 7 centimeters in the neural-based method. Thus, precise of building of LAM by neural-based method is in 2.7 times higher than precise of existed method. The precise of LAM by neural-based method, can be explained by high precise approximation of sensor readings in presence of noises, unlike an existed method that just “trust” completely to each sensor readings.

6. CONCLUSIONS
In this article it is offered and experimentally explored the new neural-based method of local area map building for navigation of autonomous mobile robot using the fusion of readings from ultrasound sensors and infrared scanner. The offered method is characterized by less algorithmic complexity and possibility of processing the sensor readings in real time in 1.5-4 times more precisely than existed method.

7. REFERENCES


