# GMDH application for autonomous cranberry harvester navigation on basis of objective function prediction

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**Abstract.** *In previous research works the authors showed possibility in principle to solve all the intellectual problems concerning the autonomous mobile robot (AMR) control with the help of group method of data handling (GMDH). In present paper an approach on optimal path planning was presented. One of the mentioned solutions is based on prediction of objective function which consists of extreme and restrictive components. Distribution prediction of objective function components' partial derivatives of path is carried out with help of modified polynomial neural network. The results of prognoses for distributions of different difficulty and different methods of data sample generation (regular and chaotic grids) are provided. Optimal path planning for autonomous cranberry harvester developed by authors is carried out on basis of obtained prognoses.*

## Keywords

GMDH, autonomous mobile robot, prediction, objective function, optimal path

## 1 Introduction

The success achieved by different scientific trends in image recognition and control of different technical objects led mankind very closely to the creation of AMRs of different purpose [1]. Nowadays, there exist many ways used for realization of such systems: artificial neural networks, fuzzy logic, genetic algorithms, autonomous adaptive control and others, and the combination of different methods [1]. In spite of many successful applications [2], usage of GMDH for autonomous robot's control is very uncommon. In the research works [3,4] the authors showed that all the intellectual problems concerning the AMR control may be solved with the help of GMDH. The application of one and the same method in dealing with different problems leads to unification of control system software modules that simplifies robot design process. On the other hand, simple conception of GMDH, according to the authors', facilitates its engineering application that is very important for development of AMR. The decision making process on optimal path planning with regard to autonomous cranberry harvester is described below.

## 2 Decision making process on optimal path planning

There was offered in papers [3,4] to set the expressions for the robot's objective functions in an explicit form, thus allowing the organization of more adaptive robot behavior in comparison to the implicit setting of functions on the design stage of AMR control system. All the conditions of self-preservation, power supply, and external mission may be expressed in the form of a complex of criterion functions from the essential variables [5]. The objective functions may depend just on these variables but also on time (for example, in case of finding the autonomous power supply function) [5]

As an objective function we will imply dependence of two components (extreme and restrictive) from different parameters (environment {W}, robot {I} and the parameters of robot link with the environment {E}). According to the robot purpose its behavior should be directed to the maximization (or minimization) of the extreme component $\varepsilon$ of objective function. Besides, the execution of the objective task is almost always restricted by the set of {r} resources. It can be shown by the expression:

$$\varepsilon \to \max; \forall r_i = const, r_i \in \{r\}, i = 0 \ldots n \qquad (1)$$

where n – is the quantity of resources that limit the objective task execution.

The meeting of all the conditions 1 for the autonomous robot is closely connected with the search for an optimal path and can be expressed as:

$$\begin{aligned} L_g &= \{l_g \in \{L\} \mid \forall i : g_i(l_g) \le r_i\} \\ L^* &= \{l_f \in \{L_g\} \mid \forall l \in \{L_g\} : f(l) \le f(l_f)\} \end{aligned} \qquad (2)$$

with $L_g$ – a set of paths meeting all the restrictive conditions $r_i$;
$g_i(L_g)$ – function of consumption i of the resource spent during the way $L_g$;
f(L) – function of efficiency estimate of the execution of objective task;
$L^*$ – required optimal path.

Thus, we start with the search for the set of solutions which meet all the restrictive conditions, afterwards, with the obtained set $L_g$ we solve the extremal problem of finding the optimal path $L^*$. In the Figure 1 there is a decision making system concerning the choosing of optimal path. The function type f(L) and g(L) influences the method of the robot control. In some problem of robot control the extreme component of the objective function may take a form of minimization (maximization) condition of instantaneous value of some variable and all the restrictive conditions also have a differential kind or may be neglected. Hence, this problem may be solved by reactive control realization. The setting of the extreme component of the objective function in an integral kind leads to necessity of deliberative control. It is determined by the necessity of solving the problems of short-term and long-term predicting and global and local planning (general task of optimal path planning).

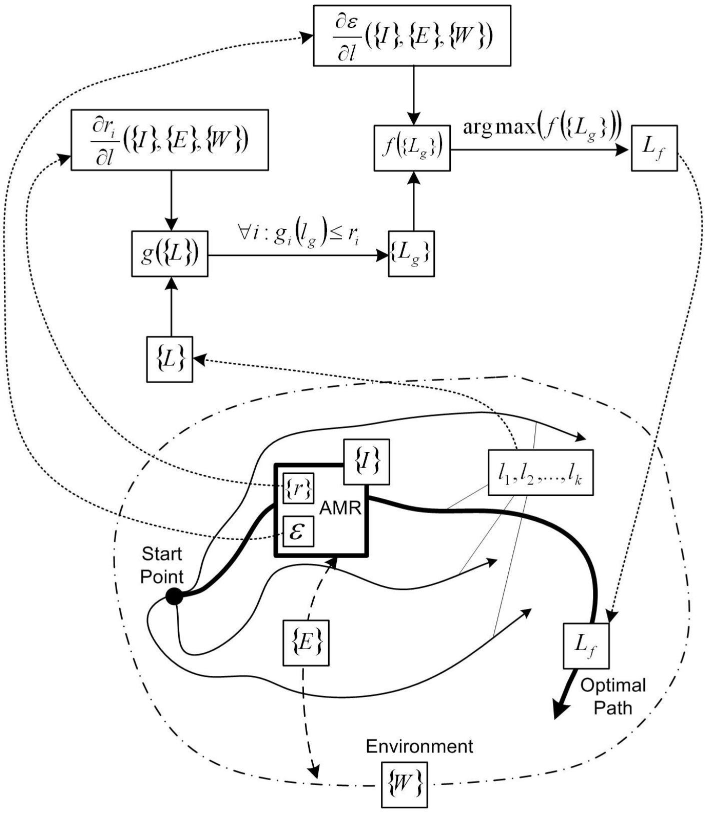


**Fig. 1.** Decision making system of optimal path planning

Parameter ε in expression 1 is always connected with the robot purpose. So, changing places of objective ε and restrictive $r_i$ parameters in 1 will result not only in the change of objective task but also robot purpose. Meanwhile, the above described approach of robot control remains invariable.

The described above approach was assumed as a basis of planning of autonomous cranberry harvester developed by authors

# 3 Autonomous cranberry harvester navigation

The functioning of cranberry harvester in the unknown environment primarily includes the stage of accumulation of knowledge and secondly - the solution of the objective task itself. Let us take as an objective function of the robot the maximal cranberry harvesting with restricted fuel consumption:

$$\begin{aligned} f(L) &= \oint_L \frac{\partial m}{\partial l} \to \max; \\ g(L) &= \oint_L \frac{\partial P}{\partial l} \le const \end{aligned} \tag{3}$$

As it was said in section 2 for realization of these functions it is necessary to follow the deliberative type of control system that can be expressed like this:

1. At the stage of data accumulation the collecting of the data is carried out about the cranberry distribution considering harvesting efficiency on path unit (extreme component of expression 3) and fuel consumption on path unit (restrictive component of the expression 3);
2. Based on the collected information the data samples are formed and predictions concerning the objective function components are made;
3. Considering the obtained prognoses the optimal path providing the execution of objective function (3) is found.

In the given experiments the following set of parameters was used. A set of environment parameters {W} includes only one parameter ρ- surface density of cranberry distribution on the bog. A set of parameters {E} robot connection with the environment includes x,y- coordinates of robot position on the territory; η, %- cranberry harvesting efficiency; P, l/km- the fuel consumption on way unit. A set of robot's parameters{I} includes V, km/h – speed of AMR movement; Q, degrees – angle of a direction of robot movement concerning the chosen positive direction of some set axis.

The extreme component here depends on the ρ, x, y, η and V parameters. Surface density ρ depends on the bog area coordinates. Harvesting efficiency η is determined by peculiarities of each concrete bog area. As the problem of the robot is maximization of cranberry harvesting, the predicted value m is the mass of cranberry harvested from the way area proportional to cranberry density and harvesting efficiency. The harvesting efficiency value also depends on the speed of robot movement. In the experiments below the speed of the robot movement is considered constant. Thus, the extreme component depends only on the bog area coordinates; hence we can talk about the surface distribution of the component $\frac{\partial m}{\partial l}(x, y)$.

The fuel consumption on the way depends not only on the speed but the movement direction Q (for example, movement up the hill and downhill). As under bog conditions anisotropy of fuel consumption is weak, so as in case with extreme component the surface distribution $\frac{\partial P}{\partial l}(x, y)$ is predicted.

The scheme of realization of the optimal path planning is shown in Figure 2. The realization in practice of the suggested general approach to the optimal path planning may be performed by introducing a priori information which allows optimizing the exhaustive search of paths. In this paper the realization of the suggested approach based on reverse sequence of operations is offered.

The maximization of extreme component value f(L) in (3) is guaranteed under the condition of the whole trace around the given bog area. However, rigid restrictions make it necessary to choose the most "interesting" from the point of objective function local areas (global navigation) for complete tracing (local navigation).

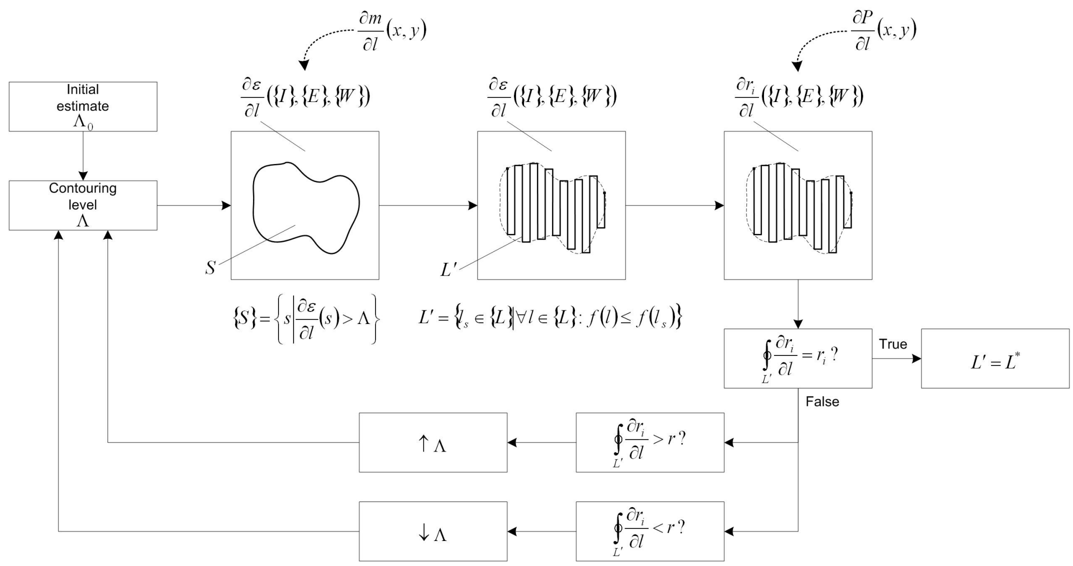


**Fig. 2.** The scheme of realization of optimal path planning

Finding of such areas can be possible on the basis of performed prognosis by mapping. Because The contours bound the areas where value of function $\frac{\partial m}{\partial l}(x,y)$ above or equal certain level $\Lambda$ (Step 1), the integral of extreme component inside these areas takes the maximal value (Step 2). The obtained path "is applied on" the function prognosis $\frac{\partial P}{\partial l}(x,y)$ to follow the restrictive condition of fuel consumption (Step 3). If the given condition is not fulfilled the parameter $\Lambda$ is changed and we go back to Step1. The increase of given level leads to decrease of the areas and the decrease – inverse effect. At the exit of this iterative algorithm we get optimal from the point of objective task execution trajectory of movement.

# 4 Experiments' results on AMR moving control

The experiment results given below concern mostly the objective components prognoses using the modified PNN of GMDH. As the quality of prediction depends on the complexity of the predicted picture of the field the authors have chosen the fields of different difficulty for the experiments. Besides, data sample for prediction were generated by emulation of robot investigation of given areas according to regular and chaotic grids. The regular grid is obtained with absence of obstacles and ideal conditions of terrain. In real conditions the grid is usually irregular (for example, some points of data sample "are dropped" given the obstacles).

When building the predicting networks as a criterion of neuron selection and layers accumulation in the network we take the variation accuracy criterion

$$CR = VAR^2 = \frac{1}{N}\cdot\frac{\sum_{k=1}^{N}(f_k - y_k)^2}{\sum_{k=1}^{N}(f_k - \bar{y})^2} \tag{4}$$

The stop of network building occurs by terms of minimal change of layer criterion value in comparison with previous layer (5) with ε=0.001:

$$CR_L - CR_{L+1} \le \varepsilon \tag{5}$$

For the network building there was made a restriction on the number of layers 8 and number of selected neurons in the layer 20. In Figure 3 you see the results of prognosis for each of the three distributions on every grid type.

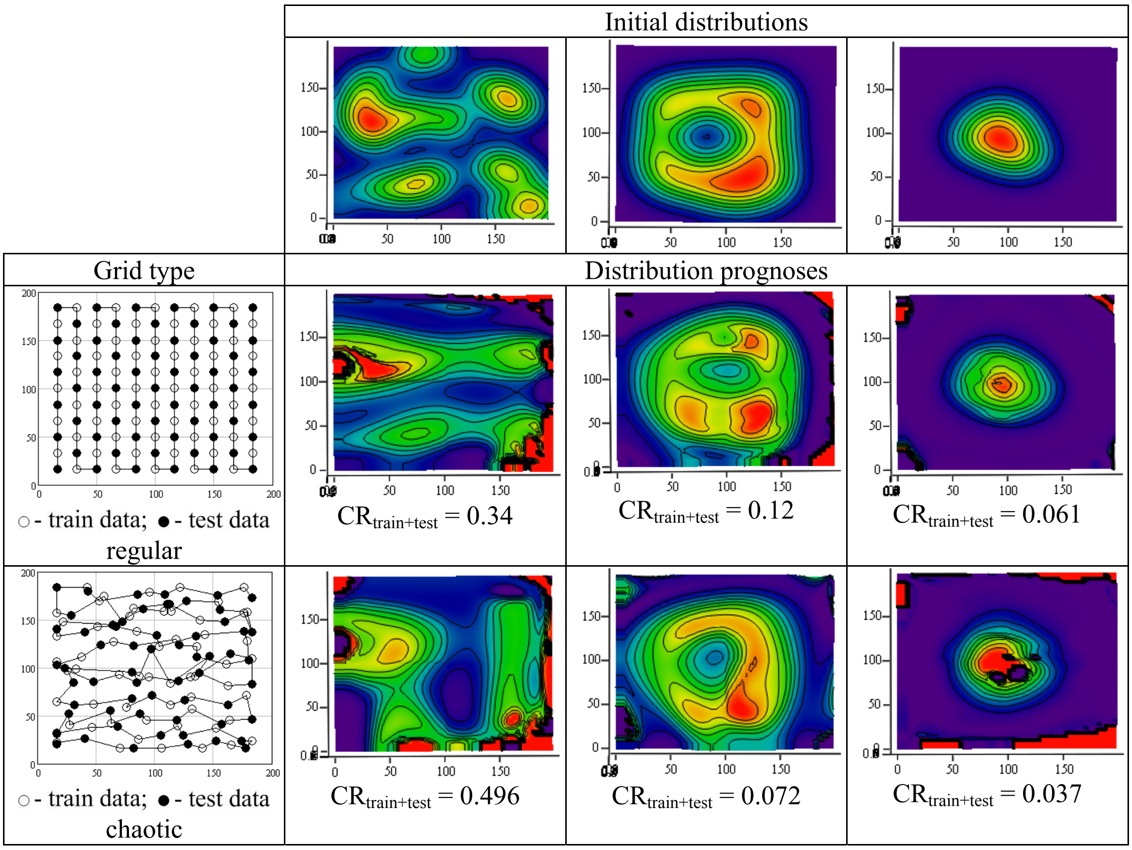


**Fig. 3.** Prognosis results on the regular chaotic grids for the three distributions

The prognosis quality can be evaluated not only visually but also due to the criterion value (4) on the whole data sample (training+testing), which was built according to the initial distribution. During the functioning of the robot in unknown environment the initial distribution will be unknown, therefore the robot will only have the data gathered at the investigation stage. In the working process the robot can use the criterion value on whole data sample.

There are prognoses given according to the being at robot's disposal data samples for extreme and restrictive components of objective function on Figure 4 (a, c) respectively. The values of whole sample criteria allow making a conclusion that the obtained prognoses are quite acceptable.

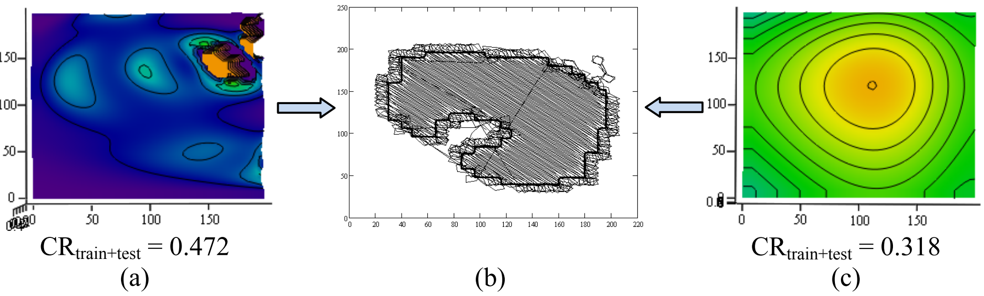


**Fig. 4.** Prognoses of distribution of extreme (a) and restrictive (c) objective function components and the result of contouring of the prognosis of objective function distribution (b)

Experiments on optimal path planning were conducted with help of program emulator. Program emulator developed by authors is a software platform which allows for general interdependences between environment and robots or robot groups. This platform is intended for realization of various configurations of AMR control systems purposely for conducting experiments on different robot control technologies practicing. Platform was implemented according to booch-OOA/OOD/OOP approach [6].

As a result of algorithm of the optimal path planning, given in the section 3, there was obtained a level of contouring $\Lambda=0.0742$ (for extremal component distribution). Using the program emulator the trajectory of robot movement was built with the deliberative control system based on the given prognoses. As the cranberry harvester refers to the class of non-holonomic robots, the local planning of moving trajectory is carried out due to the robot kinematics described by Dubins's model [7] (turning radius was equal to 5 meters)

The result of contouring and moving trajectory is given in Figure 4 (b). These results prove the workability of approach described in section 3.

## 5 Conclusion

The area of future work is experimental research on optimal path planning of autonomous cranberry harvester with different objective functions which imply realization of control systems of both reactive and deliberative types.

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