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THE HYBRID METHOD OF PATH PLANNING IN NON-DETERMINED ENVIRONMENTS BASED ON POTENTIAL FIELDS

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ABSTRACT

In this paper, we describe the results of research on the planning of vehicle paths using a modified method of potential fields. A number of structural solutions for the modification of this method are proposed. In order to choose the most suitable solution, we carried out an analysis of the influence of various parameters of the method on its functionality. The concept of a local minimum of a virtual field is given as the main factor limiting the scope of using of artificial potential fields. Here we describe in detail and analyze the types of areas of local minima in which the path planning task cant be solved without modifying the method of potential fields. Based on the analysis results, an algorithm was developed for the getting vehicles out such areas using the ant optimization algorithm and virtual goals. The efficiency of this algorithm is confirmed by simulation of the process of vehicle motion in nondeterministic environments with extended obstacles of non-convex form.

Keywords: vehicle, path planning, hybrid approach, ant algorithm, local minima, virtual goal, non-deterministic environment.

1. INTRODUCTION

Currently, the improvement of path planning systems of autonomous vehicles is carried out in three areas: improving the adequacy of vehicles' models and the completeness of environment description; the assessment of variations in environment and vehicle states with the subsequent adaptation of control system parameters to its results; the use of combined (hybrid) approaches to the vehicle path planning.

To date, there are significant scientific results in the development of vehicle and environment models and in the assessment of their state. But still, the hybrid approaches to the path planning are not sufficiently developed. The most well-known works devoted to the improvement of path planning explore the basic path planning methods navigating through the environments with stationary obstacles of a simple form. For cases, when vehicles function in complex environments, some hybrid approaches are offered.

In [1] the approaches to planning implemented by the method of potential fields are considered. To specify the field, Euclidean distance, exponential and logarithmic functions are used. The existing problem of getting vehicles in local minima of the field is solved in two ways. The first method involves the creation of subsidiary goals on vertices of the polygons describing obstacles. The second one is to apply a hybrid approach. If the planning system detected the getting in a local minimum of the field, then it switches to the situational control in which the most effective motion mode is selected to bypass the obstacles.

The authors of [2] offer to randomly change the direction of the repulsive force when a vehicle gets into a local minima of virtual field and to apply virtual goals which replace global goal as long as the vehicle will be avoiding an obstacle.

In [3], the authors combined several methods based on the use of Voronoi diagrams, visibility graph and the method of potential fields to find a compromise between the safest and the shortest path.

The main idea of [4] is to formulate the task of path planning as an optimal control problem. The authors present the theoretical and experimental research with simulation and the optimal path planning of a mobile robot in a non-deterministic environment. The robot is described by its nonlinear mathematical model. To avoid collisions with obstacles, the method of potential fields is used.

The authors of [5] solve the task of optimal path planning of mobile robots by optimizing the coefficients of potential functions with a genetic algorithm. The optimization concerns only the parameters of attractive force in order to minimize the length of the path, and the repulsive forces are not modified. The advantage of the hybrid algorithm is that the situation of a vehicle getting into a local minimum of the field does not appear because there is always an alternative way of the vehicle motion.

In [6], the path planning is based on a hybrid A*-algorithm which allows building the smooth motion paths considering restrictions. To smooth the planned path, the combination of the method of potential fields and Voronoi diagrams is used. The authors presented the results of field experiments confirming effectiveness of the approach.

A combination of the method based on Voronoi diagrams with other methods proposed in [7] results in the vehicle trying to move to the most unexplored and free from obstacles environment areas. There are also approaches, not simply combining Voronoi diagram with other methods, but also modifying it. For example, the path planning based on a generalized Voronoi graph in an unknown environment is presented in [8].

In [9], the global dynamic window method is combined with a fast obstacle avoidance method from [10] and with a global navigation function NF1 [11] which has no local minima. This function is based on the wave algorithm generating wave propagation from the target point.

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The above-listed methods are widely used in combination with a method of potential fields [1, 11, 12] and search methods such as the A*-algorithm for a complete mapping in known environments or the DF*-algorithm [12, 13] used for mapping in uncertain environments.

In [14], a combination of the dynamic window, the elastic band and the global navigation function NF1 is presented. This approach ensures the formation of smooth safe paths, except for the motion in narrow passages in close proximity with other vehicles.

2. STRUCTURES OF HYBRID SYSTEMS OF PATH PLANNING

For the successful path planning, information about the location of obstacles, the goal of mission, and the initial conditions should be available on the system input. The volume of this information will vary depending on the used method or approach to the vehicle path planning. For example, if the method of potential fields is used, then only information about the coordinates of the nearest obstacles, the vehicle current coordinates and orientation, and the goal coordinates will be enough. Such volume of information is not enough for methods based on the behavioral approach with fuzzy logic. In this case, the complete cloud of points belonging to obstacles from a vision system is needed.

At the output of the path planning system, the vehicle desired position and orientation are formed. Also, some of the methods and approaches make it possible to obtain not only a set of coordinates and orientation angles, but several sets or even a full desired path, as well as the vehicle velocity and acceleration on the path.

Depending on the characteristics of a vehicle and its operation environment, the path planning system can be built basing on the single module (Figure-1*a*) and multi-module (Figure-2*b*) principles.

In systems based on a single function module, one basic path planning method is used, and multi-module systems consist of several such methods. Also in multi-module systems some modules may function for tuning the parameters of basic methods during the path planning process. From here, the multi-module systems of path planning will be called hybrid systems.

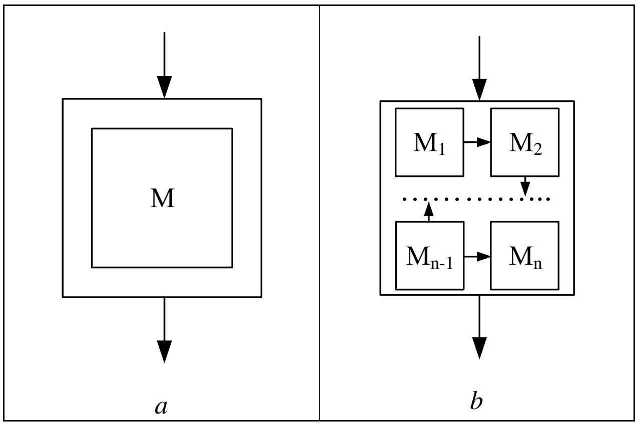

Figure-1. Types of path planning systems: *a*- single module; *b*- hybrid.

Depending on the nature of functional modules interaction, two types of hybrid path planning systems can be distinguished. The first type includes the systems in which the character of input and output information of each module is the same (Figure-2). In such systems each module performs complementary functions for other modules.

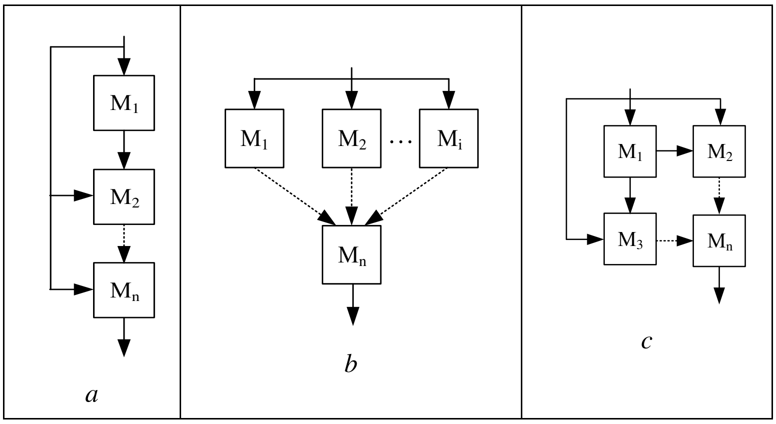

Figure-2. Structures of hybrid systems of the first type.

Figure-2*a* shows the serial structure of hybrid path planning systems. As it can be seen, the outputs of preceding modules are inputs to subsequent modules. For example, on this basis one can construct a path planning system based on the D*-algorithm and the method of potential fields. In such a system, the desired path of a vehicle is generated with the help of the D*-algorithm. The points of this path will be goals for the method of potential fields.

Figure-2*b* shows the parallel structure of hybrid path planning systems. As it is seen, the outputs of the modules are inputs to the module M_n. For example, on this basis one can construct a path planning system based on the behavioral approach. The modules M_1, M_2, ..., M_i

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implement some basic behaviors and the module M_n performs coordination.

Figure-2*c* shows the mixed structure of hybrid path planning systems which, obviously, is the most difficult to implement.

In path planning systems of the second type, the modules modifying the parameters of other modules or input data can be distinguished (Figure-3)

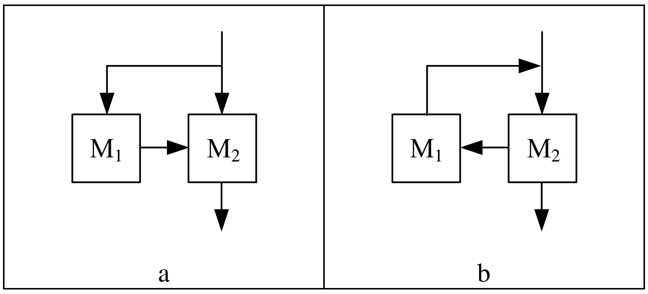

Figure-3. Structures of hybrid systems of the second type.

Figure-3*a* shows the hybrid planning system in which the module M_1 modifies parameters of the module M_2 implementing one of the basic planning methods. For example, in such a way we can construct a path planning system based on the method of potential fields with modification of parameters of virtual forces by a controller with fuzzy logic.

Figure-3*b* shows the hybrid planning system in which the module M_1 modifies input information of the module M_2. In the module M_2, one of the basic planning methods is implemented. For example, so we can construct a path planning system based on the method of potential fields in which a special algorithm modifies information about the location of obstacles.

Obviously, modules can operate at different sampling periods in hybrid path planning systems. This makes it possible to reduce the computational cost of the planning by activation of some modules with new information about the location of obstacles. On the other hand, it requires the coordinated functioning of modules.

3. PATH PLANNING MODULE BASED ON VIRTUAL FIELDS

The method of potential field is a common method of the vehicle path planning due to the fact that it has a number of advantages:

- low requirements to the onboard computer;
- low requirements for the sensor subsystem;
- the possibility of using inaccurate (approximate) information about coordinates obstacles points;
- wide opportunities for modification.
- But along with the advantages this method has the following disadvantages:
- possible areas of a field local minimum in which the vehicle can not continue to move to the goal point;
- low efficiency when used in three-dimensional environment and in flat environments with difficult obstacles;
- does not take into account the vehicle dynamics and sometimes, as a consequence, the planned trajectory can not be implemented.

The above listed shortcomings make independent use of this method for the vehicle path planning in non-deterministic environments difficult, but opportunities for modification allow synthesis of hybrid planning methods eliminating disadvantages of this method.

In this section, we consider nonpotential field as repulsion forces will depend on velocity and therefore will be non-conservative. Therefore, from here we will talk about virtual fields. Figure-4 shows the effect of virtual forces on the vehicle.

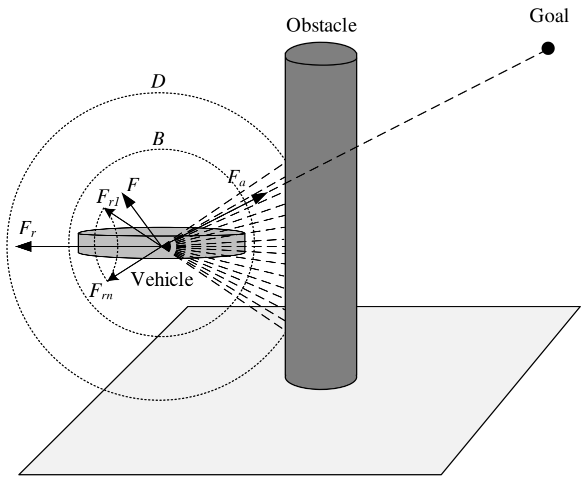

Figure-4. Impact of virtual forces on vehicle.

Vehicle motion to the goal goes under the influence of the attractive virtual force F_a. The points of the obstacle got within the range of the sensor system emerge the virtual repulsive forces F_{ri} with the resultant repulsive force F_r. The direction and magnitude of the resultant force F determine the further motion of the vehicle.

Since all virtual forces are usually applied to the center of mass or the center of symmetry of a vehicle, it is necessary to introduce a certain safety zone B around the vehicle and take it into account when tuning the coefficients of virtual forces. Also, sometimes, it is advisable to introduce the range D of action of the virtual repulsive forces which is less than the range of the vehicle sensor subsystem. Outside this area, the virtual repulsive forces do not act. This is to not consider the impact of the obstacles that are at a significant distance from the vehicle.

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At any time during the vehicle motion to a goal, the components of the virtual attractive force are calculated in accordance with the expression

$$\begin{bmatrix} F_{aX} \\ F_{aY} \\ F_{aZ} \end{bmatrix} = \frac{k}{d_g}\left(\begin{bmatrix} x_g \\ y_g \\ z_g \end{bmatrix} - \begin{bmatrix} x \\ y \\ z \end{bmatrix}\right)$$

where d_g is the distance between the vehicle and the goal $\left(d_g = \sqrt{(x-x_g)^2 + (y-y_g)^2 + (z-z_g)^2}\right)$; k is a coefficient (k>0); x, y, z and x_g, y_g are the coordinates of the vehicle and the goal.

The components of the virtual repulsive force are calculated in accordance with the expression

$$\begin{bmatrix} F_{riX} \\ F_{riY} \\ F_{riZ} \end{bmatrix} = c \cdot v \cdot \exp(-b \cdot d_i) \cdot \begin{bmatrix} v_{ix} \\ v_{iy} \\ v_{iz} \end{bmatrix} \qquad (1)$$

where v is the vehicle velocity; d_i is the distance from the vehicle to the i-th point of an obstacle $\left(d_i = \sqrt{(x-x_{oi})^2 + (y-y_{oi})^2 + (z-z_{oi})^2}\right)$; c, b are coefficients (c>0, b>0); v_{rox}, v_{roy}, v_{roz} are the components of the vector

$$v_{ro} = [x_{oi} - x, y_{oi} - y, z_{oi} - z]^T,$$

on the axes of a fixed coordinate system.

In contrast to the description of repulsive forces using trigonometric, hyperbolic, logarithmic expressions, their representation as (1) allows more flexible tuning by changing the magnitude (the coefficient c) and the degree of attenuation (the coefficient b).

Figures 5 and 6 show the effect of the coefficients b and c on the character of the field reduction. We can see that small changes in values significantly affect the magnitude of the repulsive force. The coefficient c will have the greatest impact near obstacles, but at a considerable distance from an obstacle the vehicle motion is most affected by the coefficient b.

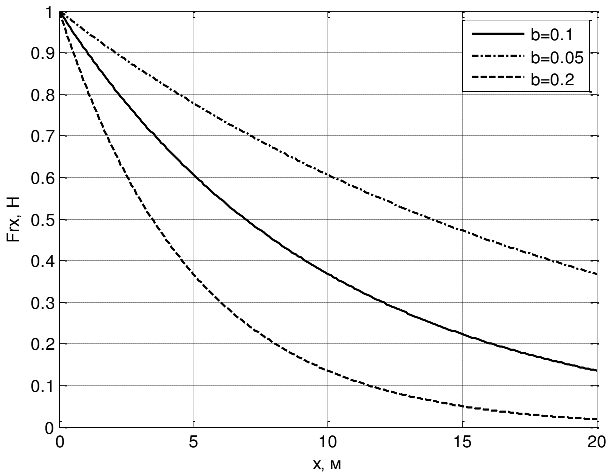

Figure-5. Effect of coefficient b on field reduction (c = 1).

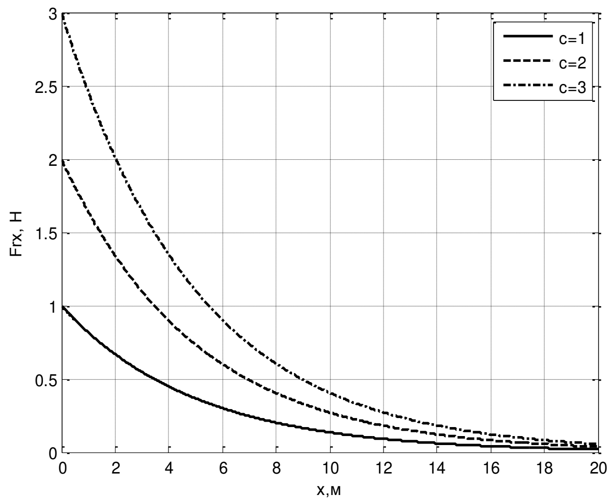

Figure-6. Effect of coefficient c on field reduction (b = 0.2).

It will be shown below how the mechanism of getting out the areas of a local minimum of a virtual field can be implemented by varying these coefficients during the vehicle motion to a goal in an environment with obstacles.

Accounting the vehicle velocity in the virtual field characteristics can improve safety of its motion at high speeds. Figure-7 shows relative motion of the vehicle and the obstacle which is inside the area limited by the range D of the virtual forces action.

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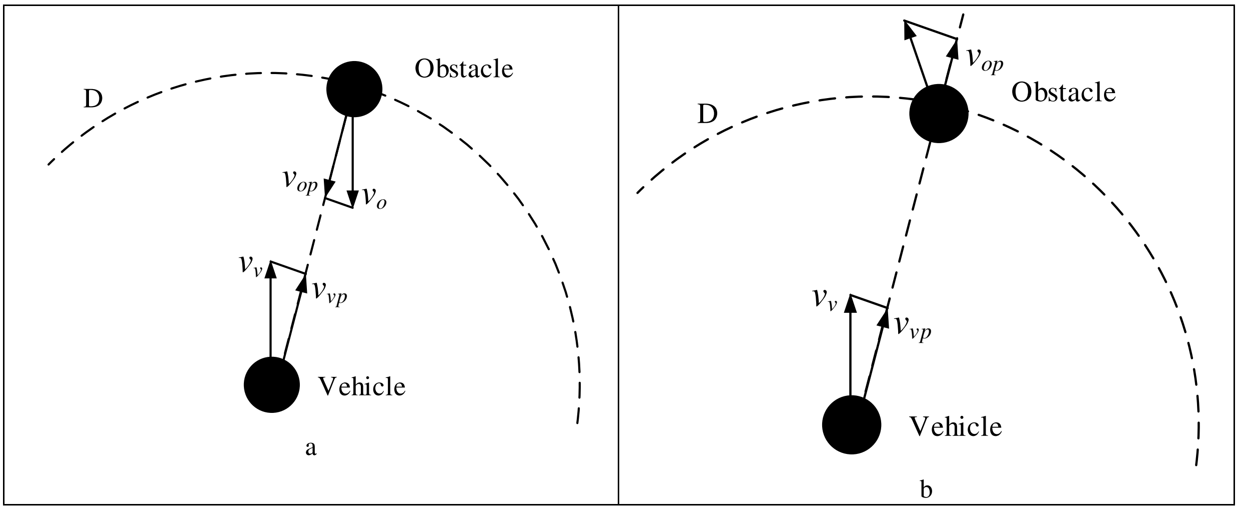

Figure-7. Relative motion of vehicle and obstacle.

Let's assume the speed of obstacle is known. Then, in the case of opposing motion of the vehicle and the obstacle (Figure-7a), it is necessary to find projections of their velocities (v_{vp}, v_{op}) on the line connecting their centers, and the coefficient v of virtual repulsive force is given by

$v=v_{vp}+v_{cp}$,

In the case of the vehicle and the obstacle moving in one direction (Figure-7b)

$v=v_{vp}-v_{cp}$.

In the latter case, if the obstacle velocity is higher than the vehicle velocity ($v<0$), then the value of $v = 1$ will be substituted in (1). If the current velocity v_{op} of the obstacle is unknown, only the velocity $v = v_v$ will appear in (1).

If the border on the operation zone is given, the virtual repulsive force will be represented similarly to (1). But a projection of the vehicle velocity on the line connecting it and the nearest point of the working area border is used as v (Figure-8).

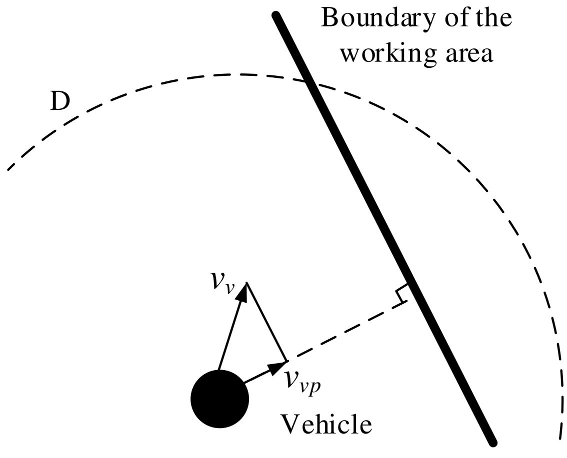

Figure-8. Vehicle motion relative to border of working area.

After calculating the force of the vehicle attraction to a goal and the forces of repulsion from the points belonging to obstacles and boundaries of the working area, the components of the resultant force of virtual field can be found as

$$\begin{bmatrix} F_X \\ F_Y \\ F_Z \end{bmatrix} = \begin{bmatrix} F_{aX} \\ F_{aY} \\ F_{aZ} \end{bmatrix} + \begin{bmatrix} \sum_i F_{riX} \\ \sum_i F_{riY} \\ \sum_i F_{riZ} \end{bmatrix}.$$

In this paper, in accordance with the recommendations of [15], the coordinates of the next point of a planned path will be found by a single integration.

$$\begin{bmatrix} x_k \\ y_k \\ z_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ z_{k-1} \end{bmatrix} + \begin{bmatrix} F_X \\ F_Y \\ F_Z \end{bmatrix} \cdot \Delta t$$

where Δt is a time step.

4. MODULE OF DIAGNOSTIC OF LOCAL MINIMA OF VIRTUAL FIELDS

The problem of local minimum in the method of virtual fields was considered in many publications [1, 2, 15, 17]. As a local minimum in the field of virtual forces we mean a certain area in which the vector sum of forces is such that a vehicle can't continue the motion towards a goal. Therefore, when the vehicle moves to the goal point, it is necessary to take additional measures for the diagnosis of getting into the local minimum.

Situations when vehicles get into local minima of field are determined by an environment configuration (size and location of obstacles), as well as by a form of the functions of virtual forces. The two-dimensional representation of such situations is shown in Figure-9.

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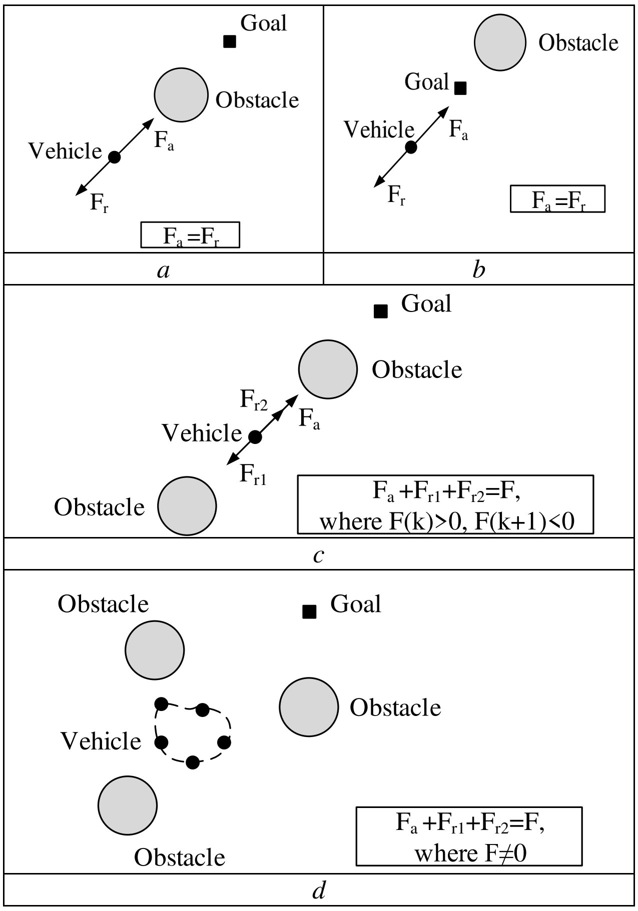

Figure-9. Vehicles getting into local minima of virtual field.

In the cases shown in Figure-9*a* and *b* the configuration of the environment and the virtual forces are such that the resultant virtual force in the local minimum is zero. The vehicle can't continue its motion to the goal. This situation can be diagnosed if the vehicle velocity is known. If in the process of motion to the goal point the velocity decreased below a certain threshold $v_{\min}$ and the motion direction is not changed, it is necessary to take additional actions in order to get it out the local minimum.

In the case shown in Figure-9*c*, the environment configuration and the virtual forces are such that the resultant virtual in the local minimum changes its direction at each time step. The vehicle executes alternating motion and can not reach the goal point. This situation can be diagnosed by analyzing the motion direction. If the direction of the projection of the resultant virtual force on the line connecting the vehicle and an obstacle at every motion step is reversed, i.e. the angle

$$\alpha = \pi - arccos\left(\frac{\left\langle \overline{F}(k)\cdot\overline{F}(k+1)\right\rangle}{\left|\overline{F}(k)\right|\cdot\left|\overline{F}(k+1)\right|}\right),$$ is less

than some small value δ, it is necessary to take additional actions in order to avoid getting into the local minimum of the field. Studies have shown, that when $\delta \le \pi/60$, the case is well diagnosed.

In the case shown in Figure-9*d*, the environment configuration and the virtual forces are such that the local minimum is a certain area in which the resultant virtual force at each step of the vehicle motion is not zero, and the trajectory is a closed curve. The vehicle moves cyclically and gets to the previous path section each few steps (Figure-10). This case is the most difficult to diagnose. We propose to save the vehicle coordinates in the last *n* motion steps in the memory to compare the current position with the data in the memory on each planning step in accordance with the expressions

$$\begin{aligned} &x_i - x \le \Delta x,\\ &y_i - y \le \Delta y,\ i=1,2,\ldots,n, \qquad (2)\\ &z_i - z \le \Delta z, \end{aligned}$$

where *x, y, z* are the current vehicle coordinates; x_i, y_i, z_i are the coordinates saved in memory; Δx, Δy, Δz are given small values.

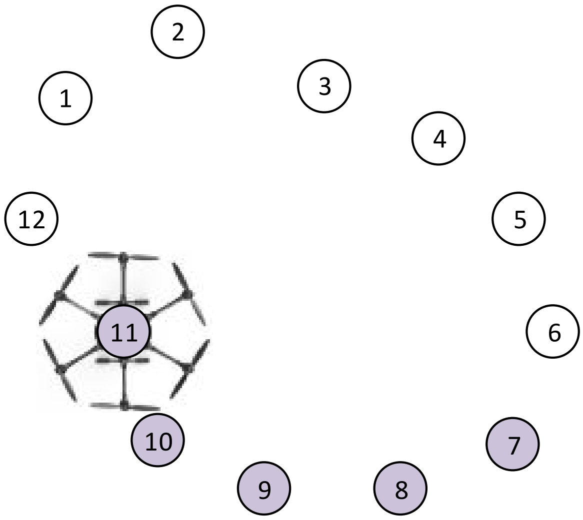

Figure-10. Application of memory to detect local minima of virtual field.

If (2) is fulfilled on the current planning step for at least one set stored in the memory, it will be necessary to increase the counter $s = s + 1$, otherwise $s = 0$. If the counter reaches the maximum value s_{max}, it will be necessary to take additional steps in order to get the vehicle out the area of a local minimum.

Our research shown that for the diagnosis of complex cyclic movements it is enough to use $s_{max} = 5$ if $m<n$. For example, the last 12 sets of coordinates are saved in the memory, i.e. $n = 12$, in Figure-10. During the motion, the counter has reached the value $s = 5$, therefore, the vehicle is in a local minimum of the field. The values Δx, Δy, Δz are should be selected on the basis of an environment size and the vehicle dynamics and size.

The analysis of different situations with vehicles getting into local minima and of used diagnostic mechanisms showed that the using of memory buffer is versatile and can be used to diagnose any of the situations presented in Figure-9. On the other hand, this mechanism

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is computationally expensive and, since it requires data saving and their analysis at each step of the vehicle path planning.

The presence of a priori information about an environment and obstacles conditions the use of a specific diagnostic mechanism. For example, in environments with single obstacles, the situations shown in Figure 9*c* and d may never appear.

5. MODULE FOR GETTING OUT LOCAL MINIMA OF VIRTUAL FIELD

To get a vehicle out a local minimum of a virtual field, different approaches are used. Some researchers introduce additional components into a repulsive force in order to change the direction of the resultant virtual force. For example, in [2] to exit local minima, a random change in the direction of a repulsion force is proposed. The repulsive force function is represented in the form of two components

$$F_{rep} = \begin{cases} F_{rep1} + F_{rep2} & \rho \le \rho_0 \\ 0 & \rho \le \rho_0 \end{cases},$$

$$F_{rep1}(X) = \eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2}(X - X_g)^n,$$

$$F_{rep2}(X) = -\frac{n}{2}\eta\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2}(X - X_g)^{n-1},$$

where ρ is the distance between a vehicle and the nearest point belonging to an obstacle; ρ_0 is the range of obstacle influence on the vehicle; X are the vehicle coordinates; X_g are goal coordinates; η, n are coefficients.

The function of repulsive force designed to get a vehicle out local minima has the form

$$F_{rep} = \begin{cases} AF_{rep1} + AF_{rep2}, & \rho \le \rho_0, \\ 0, & \rho > \rho_0, \end{cases} \tag{3}$$

where $A = \begin{cases} \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} & \theta = \pi \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & 0 \le \theta \le \dfrac{\pi}{2} \end{cases},$

θ is the angle between the force of attraction to the goal and the repulsive force, α is a random value from the interval

$$\left[0;\ \frac{\pi}{2}\right].$$

The disadvantage of this approach is that the use of a random variable in (3) leads to a sudden and sharp movements of the vehicle. In addition, it does not guarantee the getting out of situations with cyclic movement of the vehicle (Figure-9*d*).

In [1], several auxiliary points located in main goal vicinity are introduced. The distance between the auxiliary points and the main goal may be fixed or tuned by a genetic algorithm. The motion path is generated according to the minimum of a criterion including the distance to the goal and to the nearest obstacle in each point of it.

In [16], the repulsion function is formed in such a way as to take into account the distance between a vehicle and a goal. This form provides the location of the global minimum of virtual field at the goal point. It should be noted that, unlike the majority of works on the subject, the authors presented expressions for calculating the coefficients of the functions of attraction and repulsion. That gets the vehicle out the local minima of the field.

The approach from [17] allows the solution of the task of the motion path planning in environments with simple obstacles located close to a goal point. As in [16], the authors of [17] obtained analytical expressions for the calculation of the coefficients of functions describing virtual fields and allowing the vehicle to avoid getting into local minima. However, the identification of conditions, in which they can be used, is required. In other case, they have to be recomputed at each step of planning. In addition, these expressions do not provide getting vehicles out the local minima generated near complex obstacles located between the goal and the vehicle.

Analysis of the known approaches shows that the introduction of additional components in a virtual repulsive force and the calculation of coefficients allow the achievement of a goal in environments with obstacles of simple form, which do not form a local minimum area with cyclic movements of a vehicle. Using the concept of virtual goals is the most effective in complex environments, but the random location of virtual goals does not always allow achieving the global goal for a time required.

When using a narrowband sensor in difficult non-determined environments, the problem of a long motion to a goal using the method of virtual fields may arise if a relatively small amount of a priori information about environment is available. A vehicle will make a large number of additional movements that do not lead to the goal. To eliminate this drawback, we propose to use the method of virtual fields with some features of ant colony behavior.

As known, the ants mark paths by pheromone when looking for food. More optimal paths will be marked with a larger amount of pheromone, because more and more ants pass on them. If ants do not move on the marked path, then pheromone disappears with a time and the path loses its attractiveness [18].

Cubic cells are distinguished in a motion space according to the proposed algorithm. The cell is marked, if the vehicle moved through it. This information is represented as a tuple

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$P=\langle q, f\rangle$,

where $q=\{x_c, y_c, z_c\}$are cell center coordinates, f is the value of a marker.

If the vehicle moves through the cell again, the value of the associated marker is incremented by the value Δf. At each step of the path planning, all values of the markers in P are reduced with a rate μ. When the marker value reaches zero, the cell will be removed from the tuple. The repulsive force (1) with a coefficient $c = f$ is assigned to each cell included in P. Thus, the more often the vehicle passes through the cell, the greater the repulsive force increases. If some area of a local minimum of virtual field is detected, the virtual goal will be assigned to the vehicle. This goal temporarily replaces the global one. The virtual goal coordinates are calculated according to the equation

$$\begin{bmatrix} x_v \\ y_v \\ z_v \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} - M \cdot \sigma \begin{bmatrix} x_g \\ y_g \\ z_g \end{bmatrix},$$

where x_v, y_v, z_v are the coordinates of the virtual goal point; x, y, z are the current vehicle coordinates; x_g, y_g, z_g are coordinates of the global goal point; $\sigma$is a coefficient determined by the nature of environment, by the configuration of the obstacles and by the ditance between the global goal and the vehicle (σ<1); M is a rotation matrix

$$M = \begin{bmatrix} c(\alpha_1)c(\alpha_2) & s(\alpha_1)s(\alpha_3)-c(\alpha_1)s(\alpha_2)c(\alpha_3) & s(\alpha_1)c(\alpha_3)+c(\alpha_1)s(\alpha_2)s(\alpha_3) \\ s(\alpha_2) & c(\alpha_2)c(\alpha_3) & -c(\alpha_2)s(\alpha_3) \\ -s(\alpha_1)c(\alpha_2) & c(\alpha_1)s(\alpha_3)+s(\alpha_1)s(\alpha_2)c(\alpha_3) & c(\alpha_1)c(\alpha_3)-s(\alpha_1)s(\alpha_2)s(\alpha_3) \end{bmatrix}$$

where α_i are angles given randomly from range ±180°; $s(\alpha_i)$, $c(\alpha_i)$ are $sin(\alpha_i)$ and $cos(\alpha_i)$.

Thus, marking the path passed and the arrangement of virtual goals allows organizing the vehicle motion in complex environments using virtual fields. Adding only marked cells in the tuple provides low computational cost of the algorithm.

Our research has shown the feasibility of the increment value $\Delta f = 0.1c$, and the reduction rate $\mu = 0.03c$ (where c is a coefficient of the virtual repulsive force (2)). For example, if $c = 1$, the vehicle will have passed through the same cell more than 10 times before the amplitude of the cell repulsive force will became equal to the repulsive forces of obstacles.

Organization of the vehicle motion can be represented as a sequence of steps:

Step 1. Calculation of the i-th cell coordinates corresponding to the current location of the vehicle.
Step 2. If the i-th cell is in the tuple P, then transition to the Step 3, otherwise to the Step 7.
Step 3. Increment of the marker associated with the i-th cell: $f_i = f_{i-1} + \Delta f$.
Step 4: Reduction of all markers in the tuple $f_j = f_{j-1}$, $j = 1, 2, ..., n, j \neq i$.
Step 5. Transition to an algorithm of local minimum diagnostics.
Step 6. Calculation of the virtual forces repulsing from obstacles and from the cells included in P and of the force attracting to the virtual goal. Transition to the Step 8.
Step 7. Adding the i-th cell to the tuple P. Setting the initial value of the marker $f_i = \Delta f$. Transition to the Step 6.
Step 8. Motion to the goal.
Step 9. The End.

6. SIMULATION RESULTS

The simulations were carried out using the model of mobile robot and the position-trajectory control system, which were presented in [19]. The start position of the vehicle had coordinates [0, 0] for all simulations. The goal position of the vehicle had coordinates [20, 20] for all simulations. Obstacles are shown as black circles

Figure-11*a* shows one of the scenes for simulation. When using the classical method of potential fields, this scene is not passable due to the presence of multiple areas of local minima (gray areas denoted by numbers 1-5). Vehicle behavior in the areas 1 and 3 corresponds to the cases shown in Figure-9*a* and Figure-9*c* respectively. Vehicle behavior in the areas 2, 4, and 5 corresponds to the case shown in Figure-9d.

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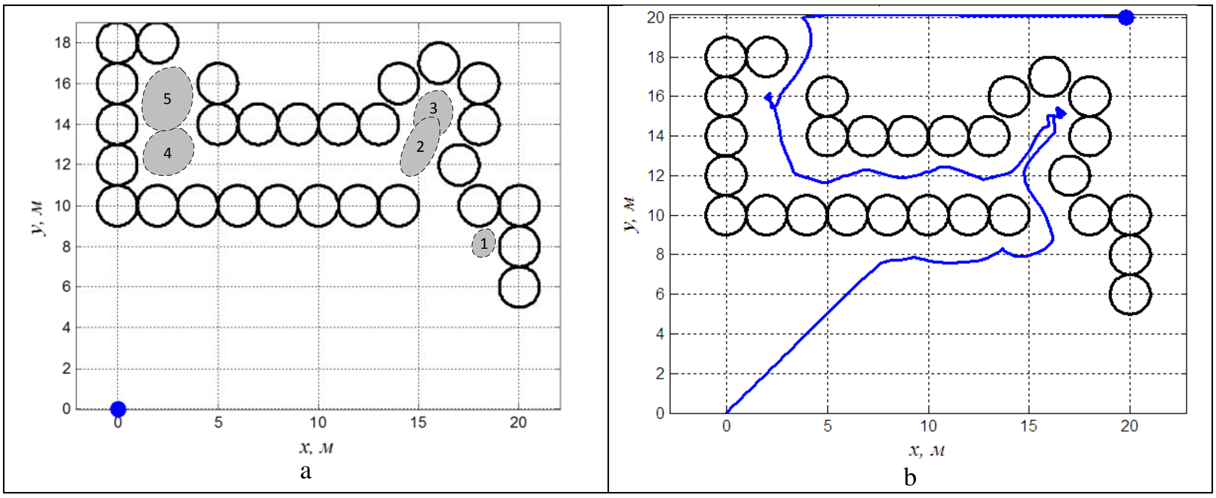

Figure-11. Scene for simulation (*a*) and path of vehicle (*b*).

The results of the simulation of the vehicle motion using narrowband radar with the angle range of ± 15 ° and the visibility range of 5 m are shown in Figure-11*b*. As it seen, the vehicle has successfully achieved the goal. Two local minimum areas (the areas 3 and 5 in Figure-11*a*) were detected, and the correct way out of them was implemented.

The random nature of the selection of a virtual goal location has led to the need to conduct multiple simulations to determine the effectiveness of the algorithm. According to the results of 20 trials on the same stage, only three tests showed inappropriate time of the goal achievement. More than 15% of time was spent on diagnostics of local minima with cyclic movement of the vehicle

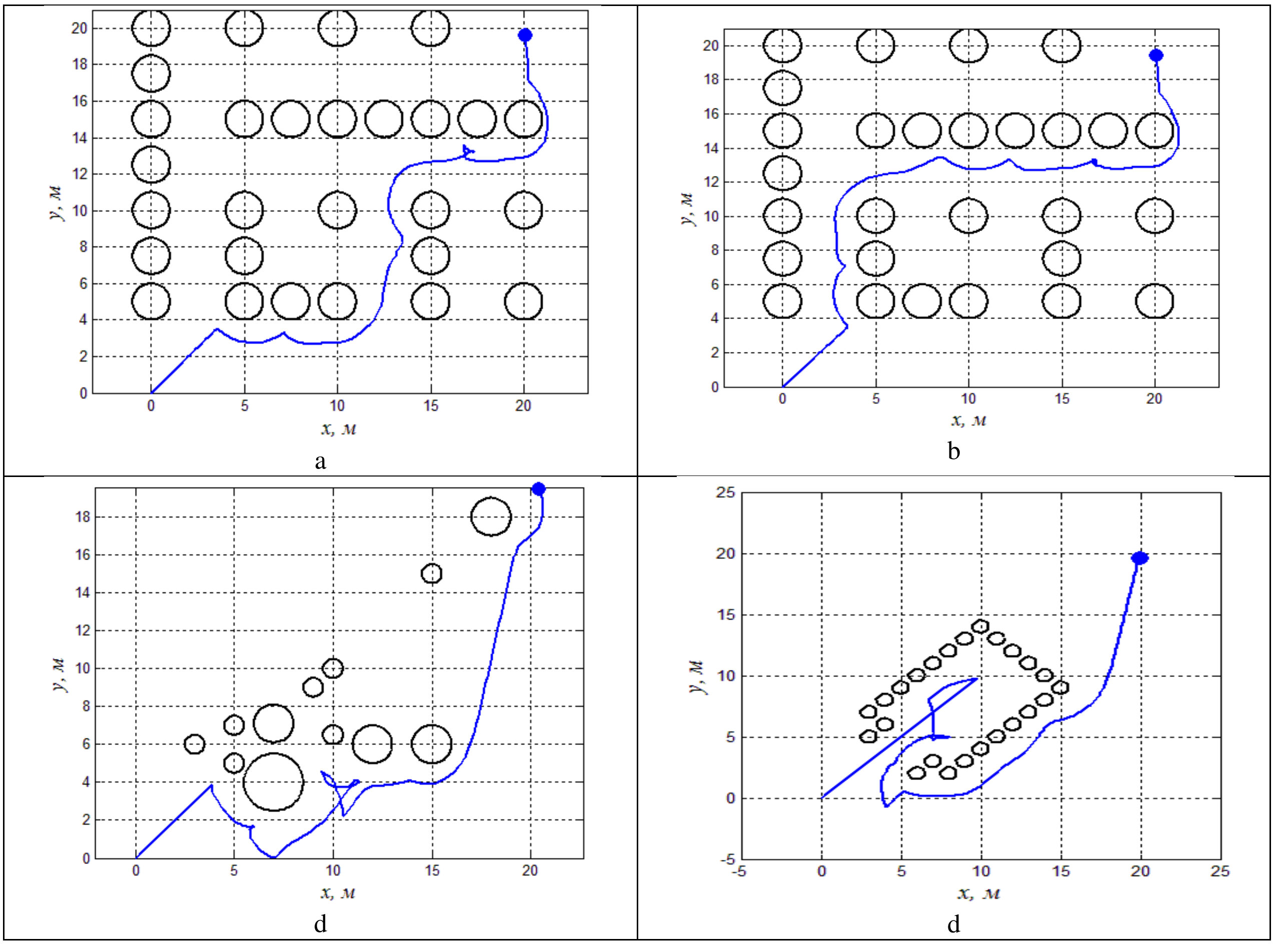

Figure-12. Vehicle motion in complex environments with stationary obstacles.

Figure-12 shows four examples of the vehicle motion to goals in environments with stationary obstacles. All goals were successfully achieved using a narrow-band locator. The most difficult task was on the scene with the "bottleneck"-obstacle shown in Figure 12*d*. The algorithm of a virtual goal placement was executed three times before the vehicle has achieved the global goal point. Figure-12*a* and Figure-12*b* demonstrate two different paths of the vehicle on the same scene that approves the random character of the proposed planning system.

The coefficient σ was set equal to 0.5 for the scenes in Figure-12*a* and Figure-12*b*and Figure-12*d* and equal to 0.25 for the scene in Figure-12*c*. Thus, for environments with deep deadlocks and long narrowness, it is appropriate to locate virtual goals further from the vehicle, and for environments with clustered small obstacles, it should be done closer.

7. CONCLUSIONS

In the bounds of this paper we presented the modification of the method of potential fields. The modification proposed by us allows solving the task of constructing the motion trajectory of a vehicle to a goal even in nondeterministic environments such as a labyrinth. This result was achieved due to a careful analysis of the properties of artificial potential fields, their limitations and shortcomings. In this paper we propose the algorithm for the getting a vehicle out the areas of local minimum of virtual field. The algorithm is based on the ant algorithm and is designed to vehicles equipped by a narrow-band locator.

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