ANNALS OF FACULTY ENGINEERING HUNEDOARA
– INTERNATIONAL JOURNAL OF ENGINEERING
Tome X (Year 2012) – FASCICULE 2 (ISSN 1584 – 2665)

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ARTIFICIAL FISH SCHOOLS IN A PATH PLANNING PROBLEM

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ABSTRACT: *The paper proposes a combination of a gradient-based path planning method and an artificial fish school based supplement for generation of a global optimal path. The optimization criterion has to guarantee „minimum path length and no collisions with obstacles". The main contribution of the paper consists in overcoming the local minima problem by self-organization of an artificial fish school in the current local minimum and its vicinity. The good performance of the proposed modified algorithm is confirmed in MATLAB simulations.*
KEYWORDS: *path planning, artificial fish school, gradient-based search, global and local optima*

INTRODUCTION

There exists a large number of methods for solving the basic path planning problem, e.g., the potential field methods, the roadmap and cell decomposition methods [5]. A path planning method that generates a global optimal path according to a criterion, which guarantees „minimum path length and no collisions with obstacles" has been proposed in Ref. [6]. It is a gradient based method minimizing the path length together with the penalties for collisions with a priori known obstacles. The penalties are produced using an approximation of obstacle-oriented repulsive potential function, made by a feed-forward neural network, trained by error back-propagation algorithm. However, due to the gradient search technique used for path length minimization, this method suffers from getting stuck in the local minima of the optimization function.

A similar path planning technique, which produces the global collision-free path between the given start and goal positions, has been used in Ref. [9] as part of a three-component system for navigation and control of mobile robots. This planning algorithm has been modified in [10] by neural network based filling the local minimum and its vicinity. Despite of the existence of many path planning algorithms how to select the most suitable approach and how to use local path-planning in collaboration with the global one - these are still open research problems.

The fish school behaviour has inspired useful ideas for solving the collision-free goal following and path planning problems [11, 8]. Several models of schooling in fish [3, 7, 12, 1, 4] have revealed that an artificial fish, which uses local information only may school in the absence of a leader and external stimuli. In these models schooling is a consequence of the tendency of the fish to avoid others that are close, to align its body with those at intermediate distances, and to move towards others that are far away. The behaviour of the fish school is different in the absence of danger (predator) and in the presence of it. When a predator appears, the individual fish behaviour becomes selfish, each individual saves itself by escaping the predator as it can. The resulting behaviour of the fish school is avoidance of the danger. Using simple behavioural rules and having no capacity for spatial orientation or memory, the virtual agents (simulated fish) are able to achieve effective collision free goal following collective behaviour.

The purpose of the paper is to propose an approach for global path planning, which is a modification of the one, presented in Ref. [6], and intends to overcome the problem with the gradient search getting stuck in the local minimum. An artificial fish school self-organizes in the vicinity of the reached local minimum and escapes it while moving to the next point planned by the basic gradient procedure. The validation of the proposed method has been carried out by means of MATLAB simulations.

THE MODEL. *Position, Speed, and Heading*

Let the artificial fish have point-like bodies, and their areas of repulsion, alignment, and attraction consist of parts of circular fields concentrically disposed in 2D environment. Time proceeds in discrete steps Δt.

At time t *an agent* i *is located at position* x_i^t *and moves with a velocity* v_i^t *during one simulation step* Δt *[4]:*

$$x_i^t = x_i^{t-\Delta t} + v_i^t \Delta t. \quad (1)$$

The velocity v_i^t is determined by the agent's heading θ_i^t (orientation of the vector v_i^t) and by the speed v_i^t (length of the vector v_i^t) as follows [4]:

$$v_i^t = \begin{bmatrix} v_i^t \cos\vartheta_i^t \\ v_i^t \sin\vartheta_i^t \end{bmatrix}. \quad (2)$$

The heading θ_i^t of the agent i is determined by

$$\vartheta_i^t = \vartheta_i^{t-\Delta t} + \alpha_i^t, \quad (3)$$

where $\vartheta_i^{t-\Delta t}$ is the agent's heading in the previous simulation step, and α_i^t is its rate of turning (angle), which depends on the interaction with the other agents (see below).

Repulsion, Attraction and Alignment

The artificial fish have three types of behavioral responses for schooling: repulsion (short distances), alignment (intermediate distances), and attraction (greater distances). This has been modeled by splitting the region surrounding the agent into behavioral zones with definite boundaries [2]. An agent triggers exactly one type of behavioral response.

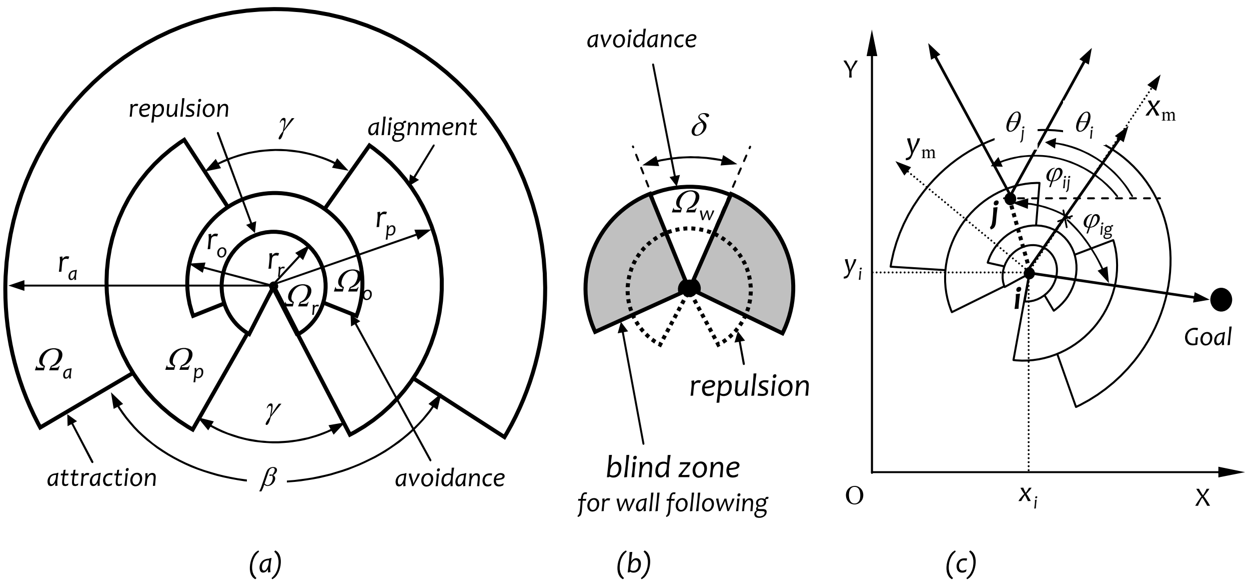

Figure 1. Behavior regions of an agent

It is shown [4] that the three behavioral responses are mediated by different sensory systems (lateral lines and visual system). Attraction, mediated by vision, operates in the whole visual range r_a around the agent except a blind area in the back with an angle β (Figure 1a). Repulsion, mediated by a similar vision system, operates over the whole visual range r_r except a blind area in the back with an angle γ (Figure 1a). For alignment the lateral line is considered to be the most important sensory system [4]. It is realized by blindfolding an additional area at the agent's front with an angle γ and with intermediate range r_p (Figure 1a).

Repulsion denotes that an agent i turns away from other agent j with a turning angle

$$\alpha_r = \begin{cases} -\alpha_{def}, & \text{if } \varphi_{ij}^t \geq 0 \quad \text{(avoid agent to the right)}, \\ \alpha_{def}, & \text{if } \varphi_{ij}^t < 0 \quad \text{(avoid agent to the left)}, \end{cases} \quad (4)$$

where φ_{ij}^t is the angle under which the agent i sees the agent j in respect to the mobile basis $\{i, x_m, y_m\}$ fixed to the body of the agent i (Figure 1c). The turning angle is chosen to be $\alpha_{def} = \pi/2$ (default turning angle, reflecting the movement capabilities of the agents). Attraction denotes that an agent i turns towards other agent j with a turning angle (Figure 1c)

$$\alpha_a = \varphi_{ij}^t. \quad (5)$$

Alignment denotes that the agent i turns in such a way that its orientation is in parallel to the heading of the agent j (by turning at an angle)

$$\alpha_p = \theta_{ij}^t = \theta_j^t - \theta_i^t , \tag{6}$$

where θ_{ij}^t is the angle between the headings of the two agents; θ_i^t and θ_j^t are the orientations of the agent i and the agent j in respect to an inertial Cartesian frame $\{O,X,Y\}$, respectively (Figure 1c).

The behavioural reaction (turning angle) of the agent i, due to the interaction with other agent j, is calculated as a discrete behaviour switching over:

$$\alpha_{ij}^t = \begin{cases} \alpha_r, & \text{if} \quad x_j^t \in \Omega_r, \\ \alpha_p, & \text{if} \quad x_j^t \in \Omega_p, \\ \alpha_a, & \text{if} \quad x_j^t \in \Omega_a, \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where Ω_r, Ω_p, and Ω_a are the regions of repulsion, alignment, and attraction of the agent i, respectively (Figure 1a,c). The repulsion behaviour of (7) depends on whether the position x_j^t of the agent j belongs to the region of repulsion Ω_r. By analogy the alignment and attraction behaviours are switched over. When the position x_j^t does not belong to these three regions the agent i does not change its orientation. The distance between the two agents is determined as $d_{ij}^t = \left\| x_j^t - x_i^t \right\|$.

In the fish school the agent i perceives more than one other agent j (by its sensors) and its behaviour is determined as the average of the turning angles caused by each of the agents j independently:

$$\alpha_i^t = \frac{1}{N_i} \sum_j \alpha_{ij}^t , \tag{8}$$

where N_i denotes the number of agents perceived by the agent i.

Goal Following, Obstacle Avoidance and Wall Following

Agents equipped with the behaviours described above (repulsion, alignment, attraction) form a fish school, which moves successfully in an environment without obstacles and without a goal position given a priori. To make the school move to a goal position, here an additional agent is proposed as an artificial "goal fish", which stays immovable in the goal position. The fish school does not influence it, but the goal agent influences the school. The behavioral regions of each agent of the school are modified by introducing an additional attractive zone for the goal fish (Ω_g), with a vision range of the whole working area. Therefore, the goal fish can be detected anywhere in the working area. Each agent responds to the goal fish by turning to it at an angle, determined by its sensor system, which covers the whole working space (without a blindfolded zone in the back of the agent) (Figure 1c):

$$\alpha_{ig}^t = \varphi_{ig}^t , \; i = 1,2,\ldots,N , \tag{9}$$

where φ_{ig}^t is the angle at which the agent i sees the goal fish g in respect to the mobile basis $\{i, x_m, y_m\}$ (Figure 1c), and N - the number of all fish in the school. For each agent this goal following behaviour is treated separately from the fish schooling behaviour (7). Therefore, the goal following behaviour is not included in (7), but takes part in (8) and modifies it as:

$$\alpha_i^t = \frac{1}{N_i + 1} \sum_j (\alpha_{ij}^t + \alpha_{ig}^t) . \tag{10}$$

The behaviour response (8) leads to forming a school that moves in a random direction, while the modified response (10) leads to a purposeful school movement to the goal position given a priori in an environment without obstacles.

The behaviour of the fish school changes critically in the presence of obstacles. Consider an environment with static obstacles. The obstacles can be positioned in a random way (i.e., they can be considered as unknown a priori). Although they are immovable the obstacle avoidance behaviour can be inspired from the fish schooling behaviour in the presence of predator. In this case the behaviour of each fish becomes selfish. The agent saves itself as it can: it forgets the goal fish to which it moves and *its interest to the other school agents decreases. It obeys the rules only to escape collisions with the other school agents, because the crowding could decrease the survival probability. For this purpose (7) and (8) become unchangeable, and the final behaviour response is obtained by combining with weight coefficients the behaviours – schooling and obstacle avoidance. The coefficients reflect the effectivness of the two behaviours and depend on the rate of danger (the shape and the size of the obstacles).*

Obstacle avoidance, mediated by additional vision, operates in the whole visual range r_o *around the agent except a blind area in the back with an angle* γ *(Figure 1a). Avoidance denotes that an agent* i *turns away from an obstacle* o *with a turning angle*

$$\alpha_{io_k}^t = \begin{cases} -\alpha_{def}, & \text{if} \quad \varphi_{io}^t \geq 0 \quad (\text{avoid obstacle to the right}), \\ \alpha_{def}, & \text{if} \quad \varphi_{io}^t < 0 \quad (\text{avoid obstacle to the left}), \end{cases} \tag{11}$$

where φ_{io}^t *is the angle at which the agent* i *sees the obstacle* o *in respect to the mobile basis* $\{i, x_m, y_m\}$ *in the range of obstacle avoidance zone* Ω_o. *The turning angle is the same as in repulsive behaviour -* $\alpha_{def} = \pi/2$. *The agent* i *can perceive more than one obstacle and its behaviour is determined as the sum of the turning angles caused by each of the obstacles separately:*

$$\alpha_{io}^t = \sum_{k=1}^{N_{o_k}} \alpha_{io_k}^t, \tag{12}$$

where N_{o_k} *denotes the number of obstacles perceived by the agent* i. *The calculation of* α_{io}^t *by (11) and (12) is conformable to the form and size of the obstacles used in simulations and to the visual range* r_o *(the obstacles are circular and their radii are equals to the visual range* r_o*). In this way simulations become simpler, and if there are obstacles at the two sides of the agent* i *(in the zone* Ω_o*) it prefers to escape the side with more obstacles. In order to be realized, the obstacle avoidance behaviour, (8) is modified as:*

$$\alpha_i^t = w_{school} \frac{1}{N_i} \sum_j \alpha_{ij}^t + w_{obst} \alpha_{io}^t, \tag{13}$$

$$w_{school} + w_{obst} = 1, \tag{14}$$

where w_{school} *and* w_{obst} *are weight coefficients reflecting the effectiveness of the two behaviours - schooling and obstacle avoidance, respectively. The goal following behaviour (10) is carried out when there is not an obstacle in the region* Ω_o, *and if it is presented, the obstacle avoidance behaviour (13) is switched over.*

In order a wall following behaviour by the fish school to be achieved, the blindfolding of the two sides of the region Ω_o *is proposed. The result is the region* Ω_w *for wall following, which is a comparatively narrow vision sector (with angle* δ*) in the front of the agent (Figure 1b). Since the obstacles are immovable, they cannot cut laterally into a moving school. If the obstacle is located in the blindfolded zones (Figure 1b) the agent does not change its heading (it neither approaches to the obstacle nor moves away from it). This tuning of the sensor for wall following behaviour is not proper for a single agent. Because of its very narrow vision sector in the front, the single agent can collide with obstacles. By schooling, the probability of someone seeing the obstacle in its narrow front sector increases and this agent will avoid the obstacle. It will influence the rest, as it will strive to pull them up aside from the obstacle. At the same time, the obstacle avoiding agent will be also influenced by the other agents, which keep their headings or try to collide with the obstacle. When the agent drifts away from the obstacle and its sensor for wall following detects nothing, the goal following behaviour starts. The probability all the agents to fall into a trap other than the goal position will decrease, because of the sliding along the obstacles in the goal direction, due to the wall following behaviour. For wall following behaviour, (11)-(14) leave unchanged. Only the vision zone and the weight coefficient are different, i.e., they are replaced as follows:* $\Omega_o \leftarrow \Omega_w$ *and* $w_{obst} \leftarrow w_{wall}$.

In the environment with obstacles and a goal, when the lifetime of the fish school is finished, the desired path can be obtained by calculating the centre of gravity of the school at each simulation step:

$$x_{aver}^t = \frac{1}{N} \sum_i x_i^t \tag{15}$$

THE PATH PLANNING. The basic path planning method

The collision-free path planning can be stated as: Given an object with a start position, a desired goal position, and a set of obstacles, the problem is to find a continuous path from the start position to the goal position, which avoids colliding with obstacles along it. The path-planning procedure proposed in this work uses the theoretical work of Meng and Picton [6]. The path for the object is represented by a set of N via points. The path finding algorithm is equivalent to optimizing a cost function, defined in terms of the total path length and the collision penalty, by moving the via points in the direction that minimizes the cost function. A two-layer log-sigmoid/log-sigmoid back-propagation neural network is used to produce the collision penalty. The surrounding area is divided into 2D grid cells and a binary value is assigned to each grid cell to indicate an obstacle presence: "0" means that the cell is fully unoccupied, and "1" - the cell is occupied. To take into account the robot's geometry the obstacles could be modified by growing their size isotropically by the robot's radius plus a small tolerance.

The x, y coordinates of the cells' centres and the corresponding assigned binary values are used as learning patterns for the 2-input/1-output neural network. The output of the network represents the collision penalty for the current position (x, y) of the object. The collision penalty of a path is defined as the sum of the individual collision penalties of all the via points. The energy function for the collision is defined as:

$$E_C = \sum_{i=1}^{N} C_i , \tag{16}$$

where C_i is the collision penalty for the i^{th} via point. The energy function for the path length is defined as the sum of the squares of all the segments' lengths connecting the via points:

$$E_L = \sum_{i=1}^{N} L_i^{\,2} = \sum_{i=1}^{N} [(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2] . \tag{17}$$

The total energy is

$$E = E_C + E_L , \tag{18}$$

The dynamical equation for a via point is chosen to make time derivative of the energy be negative along the trajectory, because the low energy implies less collisions and a shorter path. The time derivative of E is

$$\frac{dE}{dt} = \frac{d}{dt}(E_C + E_L) = \sum_{i=1}^{N} (\frac{\partial L_i^2}{\partial x_i} + \frac{\partial C_i}{\partial x_i}) \frac{dx_i}{dt} + \sum_{i=1}^{N} (\frac{\partial L_i^2}{\partial y_i} + \frac{\partial C_i}{\partial y_i}) \frac{dy_i}{dt} . \tag{19}$$

Let

$$\begin{aligned} \frac{dx_i}{dt} &= -(\frac{\partial L_i^2}{\partial x_i} + \frac{\partial C_i}{\partial x_i}) \\ \frac{dy_i}{dt} &= -(\frac{\partial L_i^2}{\partial y_i} + \frac{\partial C_i}{\partial y_i}) \end{aligned} , \tag{20}$$

then

$$\frac{dE}{dt} = -\sum_{i=1}^{N} [(\frac{dx_i}{dt})^2 + (\frac{dy_i}{dt})^2] < 0 . \tag{21}$$

$dE/dt = 0$ if and only if $dx_i / dt = 0$ and $dy_i / dt = 0$. Therefore, all via points move along trajectories, decreasing the energy, and finally reach equilibrium positions. In (20)

$$\begin{aligned} \frac{\partial C_i}{\partial x_i} &= f'(I2) \sum_{j=1}^{S} W2_j f'(I1_j) W1^x{}_j \\ \frac{\partial C_i}{\partial y_i} &= f'(I2) \sum_{j=1}^{S} W2_j f'(I1_j) W1^y{}_j \end{aligned} , \tag{22}$$

where C_i is the output of the network, $I2$ is the input of the output layer neuron, $I1_j$ is the input of the j^{th} hidden layer neuron, S is the number of hidden layer neurons, $W1^x{}_j$ is the weight coefficient of the input "x" with respect to j^{th} hidden layer neuron, $W2_j$ is the weight coefficient of j^{th} hidden layer *neuron's output with respect to the output layer neuron. From (20) and (22), the dynamical equations for x_i and y_i are derived as:*

$$\frac{dx_i}{dt} = -[2x_i - x_{i-1} - x_{i+1} + f'(I2)\sum_{j=1}^{S} W2_j f'(I1_j) W1^x{}_j]$$
$$\frac{dy_i}{dt} = -[2y_i - y_{i-1} - y_{i+1} + f'(I2)\sum_{j=1}^{S} W2_j f'(I1_j) W1^y{}_j]. \quad (23)$$

The suggested modification

When the gradient search (23) sticks in a local minimum, the resultant path comprises points, lying on an obstacle, or the segment, connecting two calculated points intersects an obstacle. The optimal path, except for going through obstacles, also (in accordance with (17)) consists of equal in size segments. As a criterion for starting the iterative procedure, modifying the basic path-planning method, the fulfillment of at least one of the following two conditions could serve [10]:

(1) The output of the neural network generates at least once a penalty for an obstacle, when at the input the coordinates of the path points calculated by the formulae (23) of the basic algorithm are given.

(2) At least two path segments exist, whose ratio is a number, bigger than a predetermined value (bigger than 1), and the neural network generates a penalty for an obstacle if the coordinates of the medium point of the bigger segment are introduced at the input.

The iterative procedure stops either after both of the mentioned above conditions are no longer met, or in case a predetermined number of iterations has been realized.

After detecting a local minimum, the search procedure is modified in the following way. With the help of the above two conditions the point is defined, after which the calculated path (a path point or a path segment) intersects an obstacle. In this point an artificial fish school self-organizes and starts to move to the next point (or the second next point) of the path outside the obstacle. That point is marked as a goal fish. The fish school stops when at least one fish of the school meets the vicinity of the goal fish. A few points of the successive fish path form the segments of an additional path, which overcomes the trap of the local minimum and goes around the obstacle. The points of the modified path serve as an initial set of point for the iteratively calculating (23) the optimal path. Usually after introducing a few obstacles, a new artificial fish school is generated which escapes the local minimum and thus the probability for successful planning a path, free of collisions with obstacles, increases.

It is shown in the literature [11, 8] that an artificial fish school using the wall-following behaviour can escape more successfully the traps around the big obstacles, than one using the obstacle avoidance behaviour. Therefore, in the path planning task under consideration, the sensory system of virtual agents (artificial fish) is adapted to the obstacle avoidance behaviour. The virtual agent is equipped with two simulated sensors located symmetrically on its fore-part (Figure 2). They detect the obstacle in the range d_{sens} in the direction of the two sensors, stimulating the neural network to calculate the penalty for existence of obstacles in these two points. If this penalty exceeds a certain threshold $S_{threshold}$, this indicates that there is an obstacle in the point (the direction).

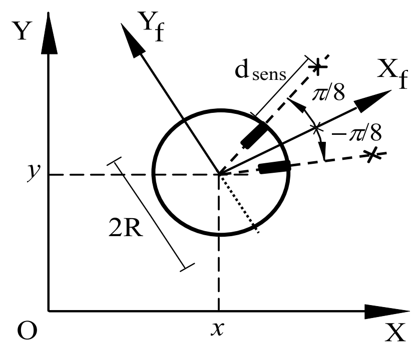

Figure 2. Geometry of a virtual agent

RESULTS AND DISCUSSIONS

The workspace consisted of two a priori known obstacles. The neural network of the path planner was trained with the error back-propagation algorithm with momentum and adaptive learning rate. The number of neurons in the hidden layer was 25. The workspace was divided into 40×40 grid cells and the neural network used 1600 training samples. After training the neural network was used to produce collision penalties needed to solve the equations (23) and thus to find a path described by a set of $N = 25$ via points (without start and goal points). The virtual sampling time was $T_0 = 0.01\,s$. The start and the goal positions were chosen to be $(0, 1.5)$ and $(2, 0.5)$, correspondingly. The initial path, needed for solution of the equations (23) was chosen as a straight line from the start position to the goal *position. Figure 3 shows the approximation performance of the neural network: (a) the surface; (b) the dotted area. In the same figure, case (b), the piece-wise liner path obtained by the described above algorithm is presented by the line with 'o'-marks and it is unsuccessful path-planning result due to the local minimum problem. All distances in the figures in this article are presented in metres.*

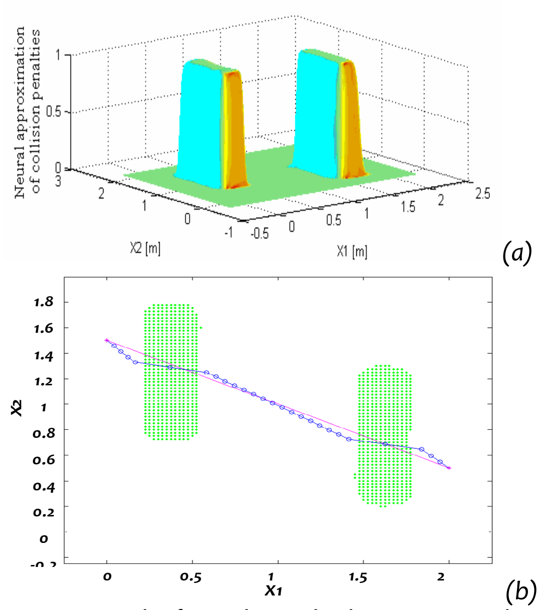

Figure 3. Results from the path-planning procedure: (a) Surface of collision penalties generated by a neural network, trained to recognize a priori known obstacles; (b) Unsuccessful path-planning procedure [10].

The experiment was repeated using the proposed modified fish school based algorithm. The fish school consisted of $N = 20$ agents. The discrete time step for fish schooling was chosen $\Delta t = 0.05\,s$. The length of the speed vector v_i^t is equal for all fish and it was set to $v_i^t = v = 0.15\,m/s$. The distances for regions of repulsion, alignment, attraction and avoidance were determined as $r_r = 0.06\,m$, $r_p = 0.2\,m$, $r_a = 1\,mm$ and $r_o = 0.1\,m$, respectively. Weight coefficients were chosen $w_{scool} = w_{obst} = w_{wall} = 0.5$. The radius and the visual range of the virtual agents used in the path planning procedure were $R = 0.05\,m$ and $d_{sens} = r_o$, respectively (Figure 2). At the beginning of the simulation, the artificial fish were put randomly in a small starting area and they were oriented randomly between 0 and $\pm\pi$. The results from this experiment are shown in Figure 4. To overcome the two local minima between the start and goal positions two artificial fish schools are produced (Figure 4a, d).

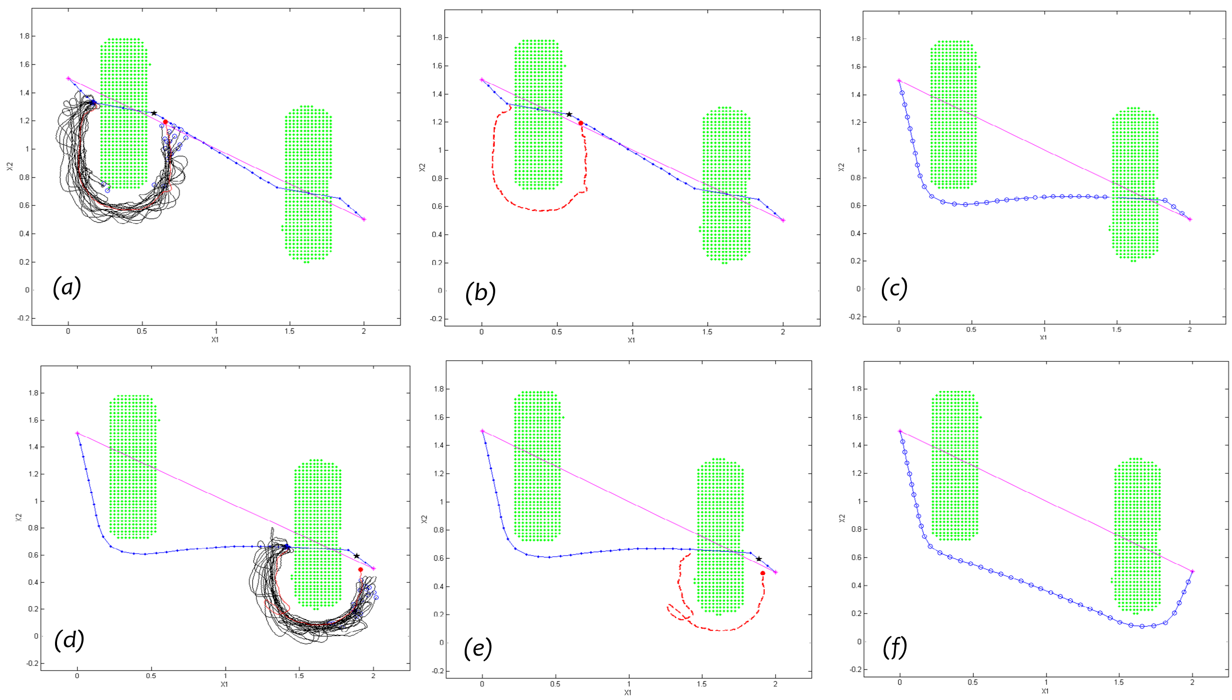

Figure 4. Results from the modified path-planning procedure

The goal positions (goal fish) of the schools are marked by 5-ray asterisks. The trajectory of the first fish, which has reached the goal fish (Figure 4b, e) was used to generate new initial points to the next iteration of the procedure (23) calculating the optimal path. The corresponding paths, medium and final, are given in Figure 4c, f, respectively. After using a new fish school, the number of via points increased. The maximum number of point is limited by $N_{all} \le 100$. When this condition is fulfilled, the number of via point must be reduced by half (e.g. by taking only odd or even points). The verification of the proposed modified path planning algorithm was carried out in MATLAB environment. The results confirmed its advantage to overcome the traps of local minima of the optimization function.

CONCLUSIONS

The paper proposes a fish schooling based method for path planning in 2D environments. It is a modification of the path-planning method presented in [6], which modification can overcome the problem of local minima of optimization function with high probability. The basic neural network in the path-planning algorithm can automatically build up the collision penalty function as an obstacles' potential function approximation. For this approximation it does not matter the number and the shape of obstacles. Future work will include an investigation on the influence of the parameters of the artificial fish school on escaping the traps of local minima.

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