Adaptive Formation Control of Robot Swarms using Optimized Potential Field Method

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***Abstract*—Robot Swarm is widely used in many applications such as forest fire detection, Search and rescue missions. Swarm of Robots is supposed to move together without collision and avoid obstacles while performing its target task. Therefore, the formation control of robot swarm is required to achieve the swarm robot target. In this paper, we present an adaptive formation control algorithm for robot swarm based on the Potential Field Method. The algorithm has three tasks, to keep robot swarm in a particular formation, avoid collision with obstacles in the environment and track a certain trajectory. An artificial neural network is employed to improve the performance of the algorithm. The network optimizes the weights in each layer then updates the potential Field parameters. A simulation via MATLAB is implemented to verify the proposed adaptive formation control algorithm. The results show that robot swarm takes less time to maintain formation, less time to track a trajectory and less time to reform again after avoiding an obstacle compared with the time in [1].**

I. INTRODUCTION

Formation of multi-robot is a form of cooperative behavior of interacting agents with a common objective [2]. In nature, formation behavior can be found in many living organisms like birds, bees, penguins, ants and fish [3]. They are moving in groups to minimize their encounters with predators and to maximize the chance of detecting predators or to more efficiently forage for food [4]. Members of swarm should move together without collisions among them and avoid obstacles while performing a certain task [5]. These properties inspired researchers in cooperative multi-robot systems. That is because of their potential applications in many areas, such as surveillance, search and rescue missions and forest fire detection [1].

In recent years, the potential field method has been widely studied. Potential Field Method was first introduced in 1985 for robot navigation [6]. Lately, it has been used for formation control of multi- agent systems [1]. The key advantage of the Potential Field Method is reducing the required information for the control algorithms as it depends only on distances between entities in the environment. Therefore, the control algorithm became efficient and integrated into a compact structure [7]. On the other hand, Potential Field Method has several limitations [8] including oscillation near obstacles and in narrow passages. Therefore, A lot of researchers try to solve these limitations. For example, Reif et al. [9] propose a Potential Field - based approach where the motion of the individual agent is a result of an artificial force imposed by other agents. Damas et al. [10] present a modified Potential Field Approach to enhance obstacle avoidance in the direction of the robots motion. Also, Howard et al. [11] divide the Potential Field into two components, a field due to obstacles and the other field due to other robots. Pathak et al. [12]also, present two Potential Field to stabilize a robot within a surrounding area. The robot is centered within a bubble (surrounding area) and then its orientation is corrected.
Furthermore, Frank et al. propose a directed potential field for motion coordination in the formation of a swarm of multi-robot system [13]. Dang et al. present a swarm-finding control based to track a moving target [14]. Shi et al. offered an artificial potential field-based approach for robot path planning [15]. Their simulation results show the effectiveness of the proposed approach. Moreover, Wang et al. propose a new algorithm based on the evolutionary artificial potential field method for mobile path planning [16]. Their algorithm is dedicated to help the robot to jump out the local minimum points. The effectiveness of the algorithm is verified via simulation.

In this paper, we propose an adaptive approach to formation control of a swarm of multi-robots for obstacles avoidance while tracking a trajectory. Our approach is based on Potential Field Method where each robot is forced by three fields, field due to obstacles, field due to other robots and field due to the target position. Artificial Neural Network is then implemented to optimize the parameters of the Potential Field Method. ANN is working beside the controller to adjust the parameters in a dynamic environment to achieve better tracking, better obstacle avoidance and a quick return to the required formation between robots in the swarm.

This paper is organized as follows: The Potential Field Method is given in the next section. Section III presents the

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optimization of Potential Field parameters using Artificail Neural Network. Simulation and results are presented in section IV. Finally, a conclusion of the proposed work and further developments are given in sectin V.

II. Potential Field Method

We consider a robot swarm of N robots ($N \geq 2$) that moves in an environment with M obstacles ($M \geq 0$). Each robot is assumed as a moving point in the two- dimensional space. The motion of the robot can be described by the dynamic equations:

$$\left\{ \begin{array}{ll} \dot{p_i} = v_i & i = 1, \dots, N \\ m_i \dot{v_i} = u_i & \end{array} \right. \tag{1}$$

Where m_i is the mass fof robot i. p_i, v_i and u_i are the position, velocity and the control input of robot i respectively. $p_i, v_i, u_i \in R^2$.

We asssume a setup of sensors to measure the positions of each robot in robot swarm, the positions of traget and the positions of obstacles in the field.and also a mean of communication between robots. The basic idea is that control force for each robot in a swarm can exert repulsive and attractive forces to other robots to keep a desired formation [13]. Moreover, other forces can be exerted on the robot, a repulsive force to keep robot away from the obstacles and an attraction force to pull the robot to a target position [13].

Thus, the control law for robot i is:

$$u_i = f^{ob}_{i,o} + f^s_{i,j} + f^t_i \tag{2}$$

A. Obstacle Potential Field

The first term in equation 2 is the obstacle field force which pushes robots away from the obstacles. The resulting obstacle force depends on the Euclidian distance between robot i and an obstacle o, $d^{ob}_{i,o}$. Where $d^{ob}_{i,o} = \|p_i - p_o\|$ and p_i, p_o are the position of the robot i and the position of obstacle o in the environment. The equation of Obstacle Potential Force is:

$$f^{ob}_{i,o} = \sum_{j \in N^{ob}_i} \left(F^{ob}_{i,o} \right) \tag{3}$$

N^{ob}_i is the set of all obstacle neighbors of robot i which is defined as:

$$N^{ob}_i = \{o, d^{ob}_{i,o} \leq r^{ob}, o = 1, \dots, M\} \tag{4}$$

Where $r^{ob} > 0$ is the obstacle detecting range. The repulsive force is given as:

$$F^{ob}_{i,o} = \Big(\big(\frac{1}{d^{ob}_{i,o}} - \frac{1}{r^{ob}} \big) \frac{k^{ob}_{p1}}{(d^{ob}_{i,o})^2} - k^{ob}_{p2} (d^{ob}_{i,o} - r^{ob}) \Big) n^{ob}_{i,o} \tag{5}$$

$n^{ob}_{i,o}$ is the unit vector from the robot i to obstacle o, $n^{ob}_{i,o} = (p_i - p_o)/\|p_i - p_o\|$. k^{ob}_{p1} and k^{ob}_{p2} are positive gains to accelerate the obstacle avoidance.

B. Swarm Potential Field

The second term in equation 2 is the swarm field force which keeps robots in a desired formation. The swarm field force is either an attractive force or a repulsive force to avoid collision between robots in the swarm. This force depends on the Euclidian distance between robot i and its neighbor robot j, $d^s_{i,j} = \|p_i - p_j\|$ where p_i and p_j are the position of robot i and robot j respectively. Each robot has neighbors defined in the set N^s_i.

$$N^s_i = \{j, d^s_{i,j} \leq r^s, j = 1, \dots, N, j \neq i\} \tag{6}$$

The swarm field force is defined as:

$$f^s_{i,j} = \sum_{j \in N^s_i} \left(F^s_{i,j} - k^s_{vi}(v_i - v_j) \right) \tag{7}$$

Where v_i, v_j and k^s_{vi} the velocity of robot i, the velocity of robot j and a damping factor respectively. If the distance $d^s_{i,j} < r^s_0$, the robots may collide so a repulsive force is needed to avoid collision between robots. r^s_0 is the minumum allowable distance between two neighbor robots. It may equal to the double of robot size.

$$F^s_{i,j} = \Big(\big(\frac{1}{d^s_{i,j}} - \frac{1}{r^s_0} \big) \frac{k^s_{p1}}{(d^s_{i,j})^2} - k^s_{p2} (d^s_{i,j} - r^s_0) \Big) n^s_{i,j} \tag{8}$$

Where $d^s_{i,j} < r^s_0$ and $n^s_{i,j}$ is the unit vector from the robot i to robot j, $n^s_{i,j} = (p_i - p_j)/\|p_i - p_j\|$. Otherwise an attractive force is needed to keep neigbor robots in the a certian distance. The attractive force is given as:

$$F^s_{i,j} = -k^s_{p3} \left(d^s_{i,j} - r^s \right) \tag{9}$$

Where $d^s_{i,j} \geq r^s_0$, k^s_{p1}, k^s_{p2} and k^s_{p3} are positive gains to accelerate the formation of the swarm.

C. Target Potential Field

The last term in equation 2 is the target field force which pulls robots to a desired position. The target potential force is an attractive force which depends on the Euclidian distance between robot i and the target position $d^t_i = \|p_i - p_t\|$ where p_t is the target position. The target force is defined as:

$$f^t_i = F^t_i - k^t_{vi}(v_i - v_t) \tag{10}$$

Where k^t_{vi} and v_t are a damping factor and the velocity of trajectory respectively. The attractive force is given as:

$$F^t_i = \left\{ \begin{array}{ll} -\frac{k^t_p}{r^t}(p_i - p_t) & \text{if} d^t_i < r^t \\ -k^t_p \frac{p_i - p_t}{\|p_i - p_t\|} & \text{otherwise} \end{array} \right. \tag{11}$$

Where k^t_p and r^t are the gain to accelerate reaching to the target and the target detecting range respectively.

TABLE I
ARTIFICIAL NEURAL NETWORK PARAMETERS

Number of neurons in input layer (K)	26
Number of neurons in 1st hidden layer (P)	12
Number of neurons in 2nd hidden layer (Q)	8
Number of neurons in output layer (R)	4

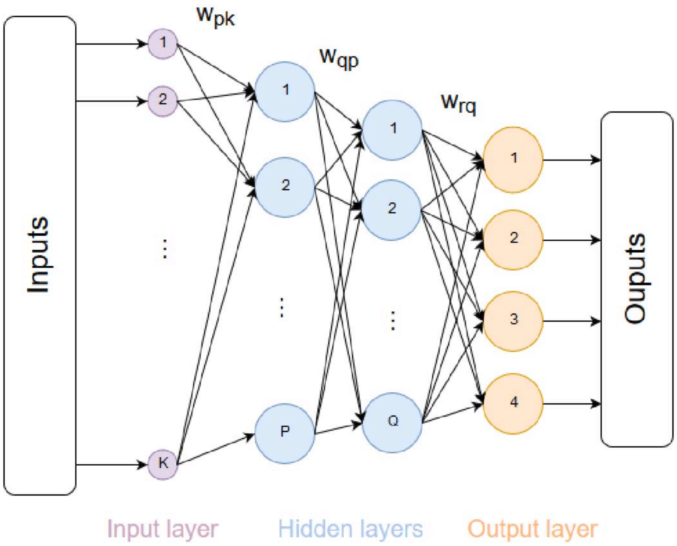

Fig. 1. Multi-layer Feedforward Neural Network with K-P-Q-R neurons.

III. ARTIFICIAL NEURAL NETWORK FOR OPTIMIZATION

Artificial Neural Networks (ANN) mimic the way biological nervous systems process the information for optimal decision making. Much of the interest of using the artificial neural networks in optimization started when it was formulated to find a near-optimal solution to a np-complete problem [17]. Since then, many problems were assigned into the artificial neural network and other variations of it [18]–[20].
The artificial neural network is used here for online optimizing the parameters of the Potential Field Method. The inputs of the ANN are the distances between robots in the Swarm, distances between robots and obstacles in the environment and the distances between robots and the trajectory. The outputs are the distances between robots and the trajectory. The hidden neurons are sigmoid and the output neurons are linear. The ANN contains two hidden layers so we can use backpropagation learning algorithm to update the weights. TABLE I shows the number of neurons in each layer. Thus, the size of ANN is K x P x Q x R. Where K, P, Q and R are the number of neurons in the input layer, the first hidden layer, the second hidden layer and in the output layer respectively as illustrated in Fig 1.

The backpropagation learning algoritm updates the weights of the ANN to minimize the error between the network outputs and the actual outputs. This error represents how the robot is far from the target trajectory. Then we relate the weights of the ANN to the Potential Field parameters so we get the optimal values to improve the performance of our approach.
We formulate the Potential Field parameters as functions in the updated weights of the ANN. Therefore, their values are updating frequently to reach the minimum distance between the robots and their target trajectory. The relation between Potential Field parameters and ANN weights are proposed as:

$$k_{p1}^{s} = \frac{10\sum_{k=1}^{K}\sum_{p=1}^{P} w_{pk}^{h1}}{K} \tag{12}$$

$$k_{p2}^{s} = \frac{2\sum_{k=1}^{K}\sum_{p=1}^{P} w_{pk}^{h2}}{K*P} \tag{13}$$

$$k_{p1}^{ob} = \sum_{p=1}^{P}\sum_{q=1}^{Q} w_{qp}^{h2} \tag{14}$$

$$k_{p2}^{ob} = \frac{k_{p1}^{o} b}{P*Q} \tag{15}$$

$$k_{p}^{t} = \sum_{q=1}^{Q}\sum_{r=1}^{R} w_{rq}^{out} \tag{16}$$

Where w_{pk}^{h1}, w_{qp}^{h2} and w_{rq}^{out} the neurons weight in the first hidden layer, second hidden layer and in the output layer respectively.

IV. SIMULATION AND RESULTS

We implement the Potential Field Method as mentioned before, build an ANN with backbropagation learning algorthim. Then, we compare between the performance of the approach with and without using ANN (before and after optimization).

A. Simulation

To verify our proposed optimization technique, we simulate the behavior of the robot swarm in MATLAB with ($N = 4$). First, we implement the Potential Field Method and add the damping term as proposes in [1]. The backpropagation learning algorithm for multi-layer ANN is implemented in MATLAB. Initial values of the Potential Filed Method parameters are set as proposed in [1] then, they are updated to reach optimal values. We run the code in two cases, case 1 without using the ANN which means without optimizing the Potential Field parameters. Case 2 Potential Field Method with ANN or with optimized parameters. Each case has two conditions of the environment, one with no obstacle and the other one with obstacles ($M = 4$).
The initial position of the robot swarm and the obstacles are given in TABLE II. The robot swarm are supposed to follow a trajectory $p_t(t) = (0.3t + 400, -0.2t + 300)$ which is the same as proposes in [1].

TABLE II
POSITION OF SWARM ROBOTS AND OBSTACLES

Robot	Initial Position	Obstacle	Initial Position
R1	(40,70)	O1	(250,140)
R2	(30,50)	O2	(250,250)
R3	(80,10)	O3	(400,160)
R4	(20,30)	O4	(400,230)

B. Results

In an environment free from obstacles, we execute the implemented algorithm. Fig 2 shows the trajectory of the robot swarm following a particular trajectory. To demonstrate the importance of the optimization phase using ANN, we compare the performance of the swarm without optimization and with optimization. Fig 3 shows the distance between robots in the swarm and the target trajectory in the two cases (without and with optimization). From the figure, we can see that the adaptive robot swarm (with optimization) follows the trajectory faster than the traditional robot swarm (without optimization). Furthermore, the adaptive robot swarm maintains formation between its member faster than the traditional robot swarm as shown in Fig 4. The figure demonstrates the distance between each robot in the swarm in the two cases. From the figure, it is clear that the time which adaptive robot swarm takes to obtain formation between its member is less than the time in the traditional one.

Moreover, We execute the proposed algorithm in a four obstacle environment. The behavior of the adaptive robot swarm is recorded in Fig 5. The robot swarm succeeds to avoid collision with the obstacles and then reforms to track the trajectory. Again, we conduct a comparison between the adaptive robot swarm and the traditional robot swarm. Fig 6 shows the distance between robots in the swarm and the target trajectory. It is evident that the adaptive robot swarm tracks the trajectory faster than the traditional one. Finally, Fig 7 shows how the adaptive robot swarm returns to its original formation faster than the traditional robot swarm, when they are avoiding the obstacles.

Thus, using ANN to optimize the parameters of the Potential Field Method enhances the performance of robot swarm. It accelerates the formation and reformation time. It achieves faster tracking to a given trajectory without collision with the environments obstacles.

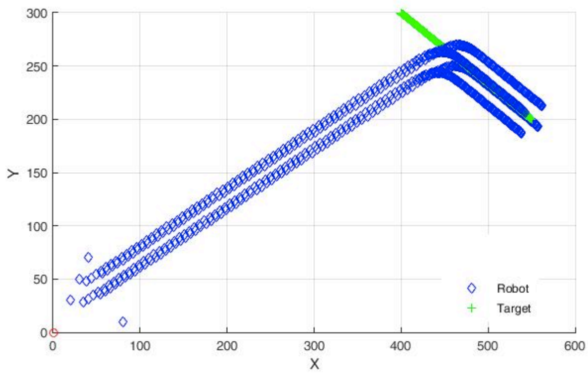

Fig. 2. Robot swarm performance in environment without obstacles.

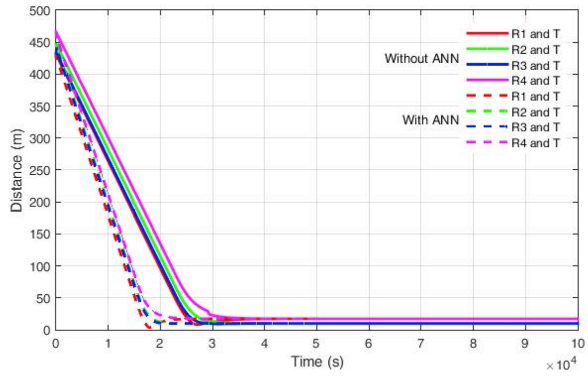

Fig. 3. Distance between robots and the trajectory before and after optimization with no obstacles in the environment.

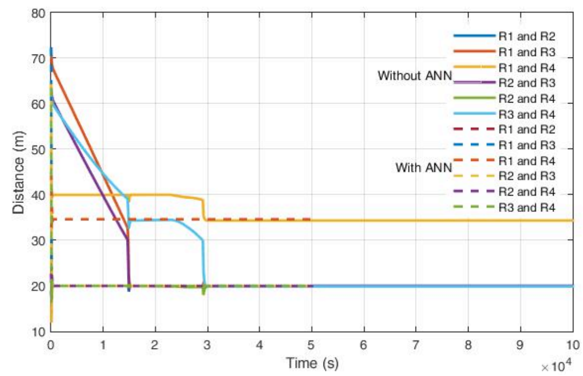

Fig. 4. Distance between each two robots before and after optimization with no obstacles in the environment.

V. CONCLUSION

An adaptive Potential Field Method for robot swarm is presented to track a trajectory and avoid obstacles while maintaining a formation. A multi-layer ANN is implemented with backpropagation learning algorithm using MATLAB. Backpropagation updates the weights of the ANN and then optimizes the parameters of Potential Field. A simulation for the Potential Field Method is performed then a comparison between the performance of the robot swarm before and after the optimization is conducted. Simulation results show that robots performance is improved after optimization. The formation time is reduced and also robot swarm returns faster to its original formation. Moreover, robot swarm tracks the trajectory faster than robot swarm without optimized parameters.

The intentional future developments for this research will be the hardware implementation of the proposed control

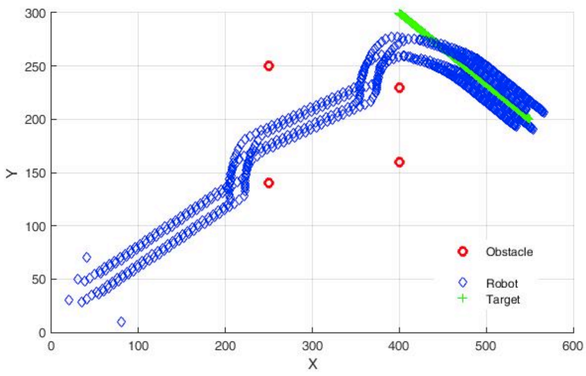

Fig. 5. Robot swarm performance in environment with four obstacles.

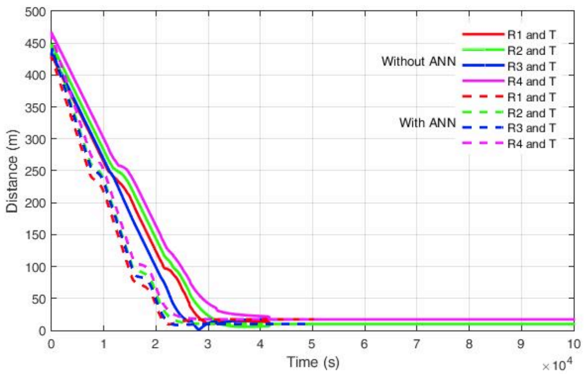

Fig. 6. Distance between robots and the trajectory before and after optimization with obstacles in the environment.

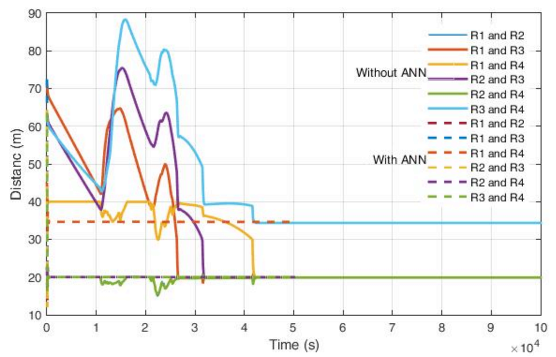

Fig. 7. Distance between each two robots before and after optimization with no obstacles in the environment.

algorithm on a mobile robot and take sensors limitation, communication delay and other aspects in consideration.

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