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Waypoint-Based Path Tracking Approach For Self-Organized Swarm Robots

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Abstract
In this paper, a waypoint-based path tracking approach is suggested for the swarm robots to follow the desired path in an organized way. In the study, the applicability of the waypoint-based path tracking on the swarm robots that show flexible and scalable behavior has been demonstrated. To evaluate the proposed path planing approach with regard to scalability and flexibility, simulations have been applied in with/without obstacle arenas with different numbers of robots and according to different lookahead distances. With the proposed approach, each swarm robots exhibit swarm behavior in an organized manner depending on the distance of the lookahead to the path to track in the with / without obstacle arenas.

Key Words
"Self organizing, waypoints, path following, swarm robots, pure pursuit method, collision avoiding"

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1. Introduction

Path tracking is one of the most important tasks for autonomous vehicles and mobile robots. Path tracking for a mobile robot is the determination of the path that a robot will travel from the starting position to the final position it will reach (J. Kim & Kim, 2020). The path tracking approach can consist of multiple points for the robot to follow to reach the target point. These points are named as waypoints (Saeed et al., 2020).

The increase in the number of mobile robots and the development of each robot's abilities to perform tasks have increased the ability of robots to perform difficult tasks by collaborating in a coordinated manner (Gong et al., 2020). In recent years, the increase in research on the collaboration of robots in multiple robot systems in a coordinated manner has been remarkable.

The robots encounter obstacles and other robots in the process of following the desired path and they are expected to reach their final positions without collision (Oliveira et al., 2013). It is aimed that the robots follow the shortest distances in the desired path trajectory and the path under the most suitable conditions according to the robot characteristics. Optimum conditions at the path tracking stage includes criteria such as robot velocity, avoidance of obstacles and robot collisions, orbital planning suitable for robot kinematics and dynamics (Chen et al., 2018).

Path tracking control approaches generally include geometric and model based (kinematic and dynamic) methods (Cibooglu et al., 2017). Geometric path tracking is based on geometric correlation between the robot and the desired path. Depending on the distance the robot will follow, the movement of the robot is determined based on the lookahead distance (Bacha et al., 2017; Cibooglu et al., 2017). Geometric path tracking methods can be done by controllers that enable the robots to move in the path orbit they will follow. The most researched and studied geometric path tracking methods are listed as Pure-Pursuit (Craig Coulter, 1990), Stanley (Thrun et al., 2006) and Vector Pursuit (Yeu et al., 2006). Pure-Pursuit algorithm is more preferred in terms of applicability and efficiency among the geometric path tracking methods. Pure-Pursuit algorithm makes geometric calculations to follow the desired path of the robot or vehicle (Lal et al., 2018). In these calculations, the robot determines its movement according to the relative position of the robot to the center of gravity of the path to be followed and applies the path tracking according to the viewpoint of the distance between the robot and the path and the heading direction of the robot. In the literature, the robot heading direction distance is called Lookahead Distance (Horvath et al., 2019). Model tracking methods provide path tracking control depending on the kinematic and dynamic model structure of the robot / vehicle in path tracking (Cibooglu et al., 2017; Patle et al., 2019). Kinematic path tracking methods use position, speed, and acceleration parameters to enable the robot to track the path. In dynamic path tracking methods, the robot behavior is determined depending on the dynamic effects of the robot along the trajectory that the robot will follow (Morgansen et al., 2007; Patle et al., 2019; Zhou et al., 2017).

Most of the work on path tracking is done with single mobile robots. The increase of work efficiency of multiple robot systems in recent years has brought the popularity of swarm robots to the fore. Multiple robot systems can consist of heterogeneous robot sets with different abilities or swarm robot sets with similar features (Bayindir & Şahin, 2007). It is noteworthy that the studies on the coordinated path tracking of the swarm robots are limited(Heo et al., 2018).

Swarm robot systems are a robotic approach that aims to perform robots with simple features by using collaboration power together (Heinrich et al., 2019). The main and the most important feature of the swarm robotic approach is that the robots move without any central control unit (Mısır et al., 2020). Robots with simple features are required to be flexible, robust and scalable during the tasks they carry out (Bayindir, 2016). Swarm robots determine their own organization according to the conditions around them and this show that they are flexible in the task they perform. Despite the increase or decrease of the number of robots their performance shows that they are scalable. The fact that the swarm robots show a strong behavior in the face of the problems they face while performing the tasks reveals their robust characteristics (Soysal et al., 2007).

The main source of motivation of this study is to demonstrate the applicability of waypoint-based path tracking on swarm robots that exhibit flexible and scalable behavior. The main contribution of this study is to examine the Pure-Pursuit path tracking algorithm in the literature on robots that move in a swarm that has simple and same features. In the study, an approach is proposed for the swarm robots to cooperate in an organized way on a desired path and to track the waypoint-based path. In this approach, the error of the path distance according to the reference trajectory is minimized by keeping the swarm motion of each of the swarm robots and it is ensured that the swarm robots reach the waypoints. The Vector Field Histogram (VFH) method is used to avoid collisions and obstacles when each robot is close enough to collide an obstacle or neighboring robots. With the proposed approach, each swarm robots exhibit organized swarm behavior based on the lookahead distance to the path it will follow. In the study, several systematic experiments have been applied to evaluate the proposed path tracking approach in terms of scalability and flexibility. These systematic experiments were carried out in a simulated environment with different numbers of robots and different look ahead distances in the with/without obstacle arena.

This paper is organized as follows; related works are explained in section 2. In the 3rd section, the proposed approach in addition to swarm robot kinematics, Pure-Pursuit and VFH methods is explained. In section 4, it includes experimental setup and problem definition. Experimental results are given in section 5. Section 6 consists of results.

2. Related Works

Path tracking studies generally focus on geometrical and model-based methods. In addition to these studies, current intuitive and evolutionary control methods are also available. In this section, studies on current path tracking are examined.

(Chandrasekhar Rao et al., 2018) have improved Krill Herd (KH) in order to create efficient path navigation by using KH behaviors. They expressed the algorithm that they developed as Improved KH (IKH). They compared KH and Differential Evolution (DE) algorithms to evaluate the efficiency of their proposed algorithm. According to their results, they reported that the HR algorithm yielded better results in the experimental and simulation environment compared to other algorithms.

In a recent study by (Lee et al., 2019) the model-based Linear Quadratic Gauss (LQG) is proposed with an adaptive Q-matrix for noise, path-related errors and problems in the process of tracing control. It is noteworthy that the proposed method is adaptable even if the vehicle technical and dynamic characteristics change. It has been stated that the experimental results obtained at various speeds give better results than other conventional path tracking algorithms.

(Wang et al., 2019) proposed model predictive control (MPC) using the fuzzy adaptive weight approach. They used MPC to monitor paths with minimal errors and to increase ride comfort during the path tracking process. With the MPC approach they have proposed, they have achieved control according to the dynamic structure of the vehicle they use. They also compared their approach with one of the other traditional approaches and achieved improvements.

(Zhang et al., 2019) study, an edible path tracking method based on Double Deep Q Network (Double DQN) is presented. The proposed approach applied the DQN based controller both with a robot used in lawn applications and in the simulation environment. They compared the Pure-Pursuit algorithm to test the performance of their proposed DQN-based controller.

(Yaguchi & Tamagawa, 2020) propose waypoint navigation that can avoid obstacle and robot collisions using the artificial potential method (APF). They proposed a new waypoint method with random priority APF method for waypoint-based path tracking method.
Shan et al. (Shan et al., 2015) proposed a new Pure-Pursuit-based method called CF-Pursuit. To reduce the fitting error with the proposed method, a clothoid "C" ^1 curve is used to change the curve used in Pure-Pursuit. This improvement has helped to reduce tracking errors in Pure-Pursuit. Compared to some other geometric controllers, the CF-Pursuit performed better in stability, tracking errors and stability.

Many studies have demonstrated that it is very difficult to achieve a balance between accuracy and stability for most traditional path tracking methods (Ohta et al., 2016; H. G. Park et al., 2018; M. Park et al., 2015).To solve this problem, (Yu et al., 2020) proposed a Pure-Pursuit based path tracking method, called Fuzzy Pure-Pursuit Control with Front Axle Reference (FPPC-FAR). The method was applied on a bus. Firstly, the reference point was moved from the rear axle to the front axle. Secondly, a fuzzy-based parameter setting method has been applied to increase the accuracy and robustness of the tracing controller. Thirdly, a feedback-feedforward control algorithm that improves speed monitoring efficiency has been designed.

(Morales et al., 2009) proposed an effective and generally applicable approach for reactive motion control, based on Pure-Pursuit and commonly used distance detection sensors. In this approach, they tried to make the control of the steering angle more precise and to soften the vehicle response by choosing the distance to look forward. An additional advantage of the approach is the possibility to use the basic Pure-Pursuit strategy as a common framework to track any combination of closed and / or open paths that can be efficient in large-scale environments.

(Bibuli et al., 2014) proposed a swarm-based path tracking guidance system for marine vehicles. The main purpose of the study is to create a formation while maintaining the distance between each other while proceeding along the path as well as the swarm approaching the desired reference path and to protect this formation along the way. The study also shows an aggregation behavior based on the virtual push / pull forces used in another aspect.

(Zhao et al., 2018) proposed self-adaptive collective motion algorithms that enable swarm robots to move towards a certain target on a pre-planned path. The proposed algorithm makes decisions using information from neighboring robots and operates without a central control. The proposed algorithm has been tested in 3 different ways. These are 1) no obstacles or leaders, 2) with a leader and no obstacle, 3) with obstacles (with and without a leader).

3. Method

In this section, waypoint-based path tracking approach is examined in cooperation of swarm robots. Pure-Pursuit is used for waypoint-based path tracking and VFH methods are used to avoid obstacle / collision. An approach that determines the behavior of each swarm robot is suggested in order for the swarm robots to follow the path in cooperation.

3.1. Kinematics of differential drive swarm robot

The modeling of a differential driven mobile robot consists of three steps: kinematic modeling, dynamic modeling and actuator modeling. Kinematic modeling deals with the geometric relations of the model and examines the mathematical structure of the motion, regardless of the effects of external forces (Buccieri et al., 2009; Campion et al., 1996; Oriolo et al., 2002). Dynamic modeling is based on the study of the movement in which forces and energies are included. The actuator must also be modeled to find the relationship between the control signal and the input of the mechanical system. As shown in Figure 1, the configuration of a differential driven mobile robot with two wheels with radius "R" placed at a distance $\frac{L}{2}$ from the robot center can be defined by generalized coordinate.

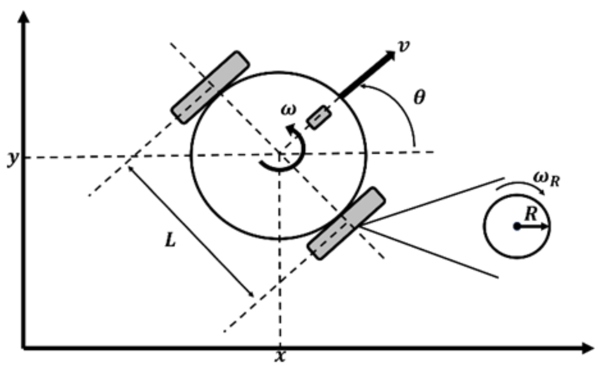


Figure 1. A two-wheeled differentially driven swarm robot and reference parameters

$$q = [x, y, \theta]^T \tag{1}$$

q, represents the generalized coordinate and using the above expression, the kinematic model is represented by Equation (2).

$$\dot{q} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta \\ \sin\theta \\ 0 \end{bmatrix} v + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega \tag{2}$$

As shown in Figure 1, v, represents the linear velocity of the robot and ω, represents the angular velocity of the robot. For the left and right wheels, there is a relationship between the angular velocity and the linear velocity of the two wheels indicated by ω_L and ω_R, respectively, as shown in the following equations.

$$v = \frac{R(\omega_L + \omega_R)}{2} \qquad \omega = \frac{R(\omega_L - \omega_R)}{L} \tag{3}$$

Here, the angular velocities ω_L and ω_R are obtained.

$$\omega_L = \frac{v - \left(\frac{L}{2}\right)\omega}{R} \qquad \omega_R = \frac{v + \left(\frac{L}{2}\right)\omega}{R} \tag{4}$$

3.2. The Pure-Pursuit method

Pure-Pursuit method is one of the most frequently used methods due to basic and superior(Cibooglu et al., 2017). It is a geometric path planing method in which the mobile robot creates a turning radius to return to the reference path (D. H. Kim et al., 2010). The main purpose of the Pure-Pursuit method is to determine the steering angle that allows the vehicle to go through this target point by determining a continuous target point on the predetermined path. In this way, the path planing problem becomes a simple geometry problem.

The rotation angle that will allow the vehicle to go through the target point is obtained as shown in Equation (5).

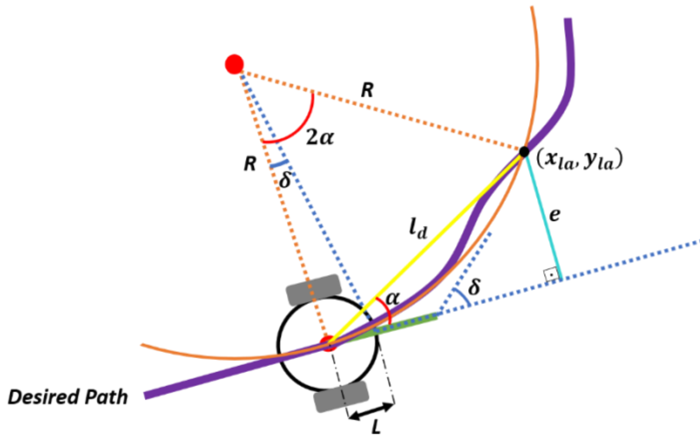


Figure 2. Geometric examination of Pure-Pursuit method

$$\delta_{pp}(t) = \tan^{-1}\left(\frac{2L\sin\left(\alpha(t)\right)}{l_d}\right) \tag{5}$$

where $\alpha(t)$ is the angle between L and l_d. l_d is the distance between the vehicle's center of axle and the target point (the yellow line in Figure 2). L is the radius of the physical structure of the robot.

Thus, the Pure-Pursuit algorithm can be identified by the pseudocode below (Chen et al., 2018).

Algorithm 1 Pure-Pursuit

1: Determine the current position of the vehicle (x, y)
2: Find the closest path tracking position to the vehicle
3: Search to target point (x_{la}, y_{la})
4: Convert the target position to vehicle position
5: Calculate the robot rotation angle for tracking target path
6: Update Vehicle Position

The parameter to be set in the Pure-Pursuit method is the lookahead distance (l_d). In this sense, l_d acts as proportional gain (Cibooglu et al., 2017). If l_d is chosen small, the vehicle tracks the path quite precisely, but the control signal, that is, the steering angle, changes rapidly, which can cause oscillations in the response (Snider, 2009). When kept large, the response becomes smoother, but in some cases large corner bends can be seen, which reduce the quality and safety of monitoring. l_d can be adjusted according to the vehicle's path geometry and speed, as shown in previous studies (Hoffmann et al., 2007; Snider, 2009).

3.3. Vector Field Histogram (VFH)

Avoiding obstacles and collisions is one of the most basic tasks in mobile robot systems. To accomplish this task, a real-time obstacle avoidance approach Virtual Force Field (VFF) algorithm has been developed by Borenstein and Koren (Borenstein & Koren, 1989) for fast mobile robots. This approach relates to the orientation of the robot in order to ensure that a mobile robot moving towards the target avoids collisions by detecting unknown obstacles. A grid map approach is used in the proposed approach. In this map, each cell occupied by obstacles creates a virtual force on the robot. In line with the virtual forces that are formed, the mobile robot tries to advance without hitting the obstacles by producing a rotation angle in the direction where the force is low. However, some deficiencies have emerged in this approach (Survey, 2005). The most important of these deficiencies is that the robot cannot move between obstacles close to each other (De Ryck et al., 2020). In order to prevent this, it has been demonstrated that a more effective control is required for local minimum and narrow transitions as well as correcting the control of the rotation angle. Borenstein and Koren introduced the Vector Field Histogram (VFH) algorithm as a new approach to solve these problems (Borenstein & Koren, 1991). VFH is an objectoriented method of avoiding obstacles. Specifically, VFH is used to represent the environment surrounding the mobile robot, and the next direction of movement is selected based on the cost function of each direction (Qu et al., 2015). The histogram shows the obstacle density seen from the robot perspective. A density of obstacles is constantly calculated in every possible direction. The direction of the robot is towards the region where the obstacle density is low. In addition, this algorithm is not concerned with kinematic and dynamic constraints (Qu et al., 2015).

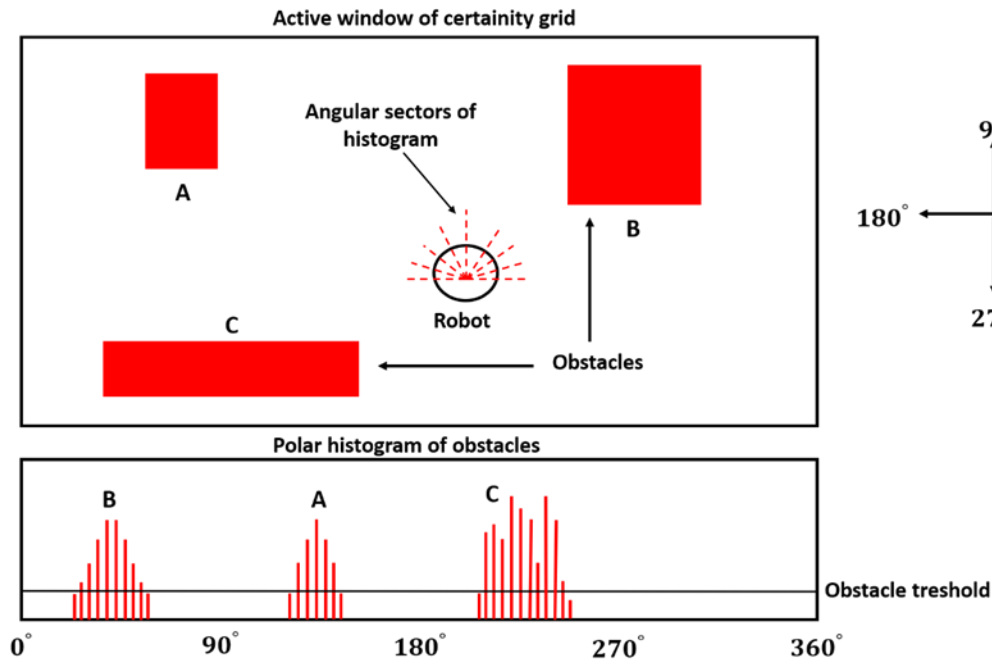


Figure 3. *Vector Field Histogram (VFH)*(Survey, 2005)

The content of each of the active cells in Figure 3 is represented as an obstacle vector at any (i,j) coordinate. The direction of the obstacle vector is obtained by the expression in equation (6).

$$\beta_{i,j} = \tan^{-1}\left(\frac{y_i - y_0}{x_i - x_0}\right) \tag{6}$$

(x_0, y_0) represents the current position of the robot. (x_i, y_i) represents the coordinates of the cell occupied by an obstacle. The magnitude of the vector in any coordinate (i,j) is obtained by the following equation.

$$m_{i,j} = C(i,j)^2\big(a - bd(i,j)\big) \tag{7}$$

Here $C(i,j)$ represents the precision value of the cell occupied by the obstacles. a and b are positive constant coefficients, and $d(i,j)$ is the distance between the robot and the active cell. The histogram consists of a series of sectors (k) at an arbitrarily chosen angle resolution (Survey, 2005). The sum of the magnitudes of these vectors, which belong to each angle sector, defines their value in the histogram.

$$h_k = \sum\nolimits_{i,j} m_{i,j} \tag{8}$$

As seen in Figure 3, the resulting histogram consists of peaks and low-value points on the histogram map according to the position and shape of the obstacle. Any histogram value that falls below a predetermined histogram threshold is defined as a candidate low-value point. The algorithm chooses the candidate low value point and moves the robot in this direction. VFH, like other potential field methods, provides a smooth control according to histogram density without any filtering (Survey, 2005).

3.4. Collaboration-based path tracking approach using Pure-Pursuit and VFH for swarm robots

The main parameter used for path tracking in the Pure-pursuit algorithm is lookahead distance (l_d). l_d is the distance from the target point determined by the vehicle for the path to be followed. Depending on the l_d of the vehicle that tracks the path, the heading direction and speed are determined. Figure 4 shows the collaboration-based path tracking approach flow chart diagram using Pure-Pursuit and VFH methods. Collaboration based path tracking approach using Pure-Pursuit and VFH provides organized path tracking of swarm robots. With the proposed approach, they can follow the predetermined path in a scalable way, depending on the number change of the swarm robots. The swarm robots that follow the paths in an organized way can exhibit flexible behaviors depending on the surrounding obstacles and conditions.

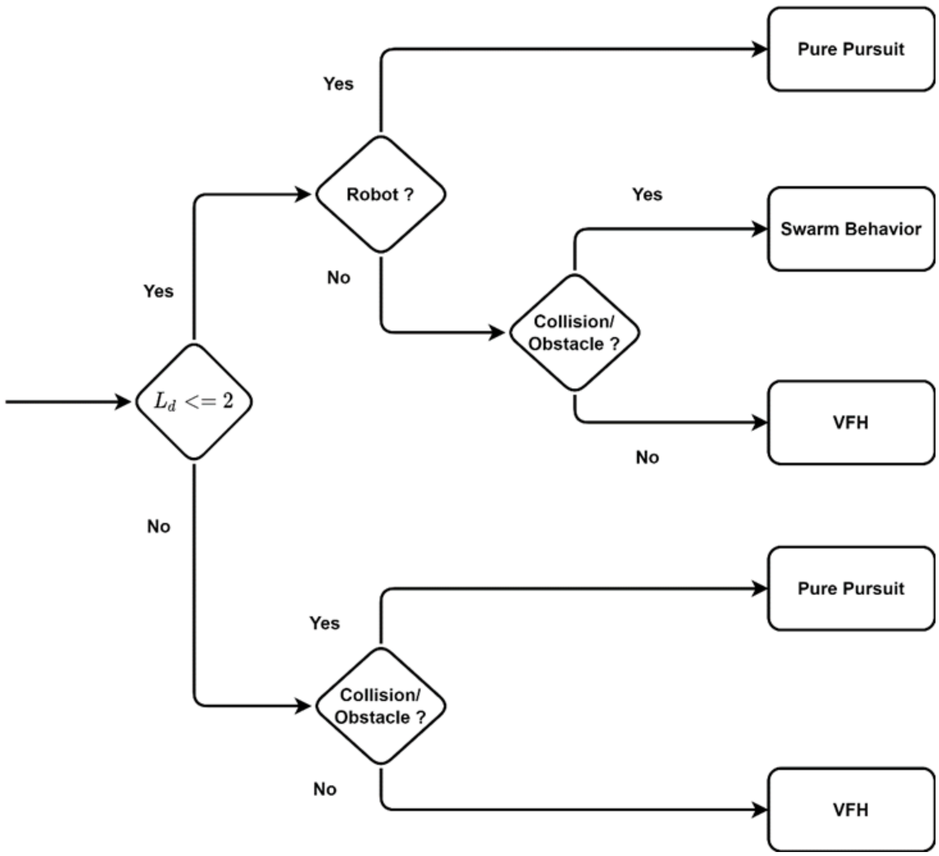


Figure 4. Collaboration based path tracking approach flow chart diagram using Pure-Pursuit and VFH

In the proposed approach, each of the swarm robots decides how path to follow, depending on l_d. Each robot checks if l_d is less than 2 units to the predetermined path. If the l_d value of the swarm robot is more than 2 units, it checks whether there is an obstacle or robot in collision distance around it. If the swarm robot encounters an obstacle or robot under these conditions, it is directed by VFH method in the direction where there is no obstacle or robot. If the swarm robot does not encounter an obstacle or robot, it follows the path with Pure-Pursuit method.

If the l_d value of the swarm robot is less than 2 units, it is checked whether there is a robot in the robot detection area. If there are robot or robots in the detection area of the swarm robot, it approaches the direction of these robots. If the swarm robot gets close enough to collide with an obstacle or robot with this condition, it moves away from the obstacle with the VFH algorithm. Otherwise, it follows the predetermined path with Pure-Pursuit algorithm.

4. Experimental Setup and Problem Definition

In this section, covers systematic experiments and results applied on a predetermined path for the proposed approach. Experiments were conducted using different robot numbers to test the scalability of the proposed approach, and different arena (with/without obstacle) conditions to test their flexible behavior. In the proposed approach, it is examined how the swarm robots influence path tracking due to the change of the value of l_d used in the Pure-Pursuit algorithm. In the systematic experiments, the number of robots, the arena conditions with and without disabilities and the value of l_d are examined for how long the swarm robots have completed the predetermined path. The experiments are carried out with the non-holonomic swarm robot shown in Table 1. Experiments are carried out in MATLAB simulation environment.

Table 1. *Swarm robot features*

Properties	***Ranges***
Robot Model	Non-Holonomic, 2 Wheels
Robot Detection	[0 8] units, 360 degree
Obstacle Detection	[0 8] units, 360 degree
Robot-robot Communication	[0 8] units
Robot radius	0.4 radian units

Each swarm robots can detect obstacles and robots within the detection range. They can detect the angle and distance information of obstacles and neighboring robots. A swarm robot can exchange data with robots within the detection range. In Figure 5 shows the swarm robot model used in the simulation environment. The swarm robot moves with a two-wheel differential drive system with a circular structure of 0.4 unit radius.

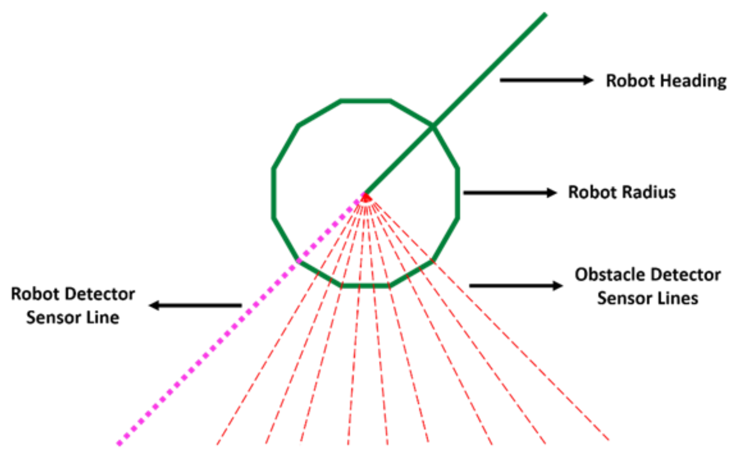
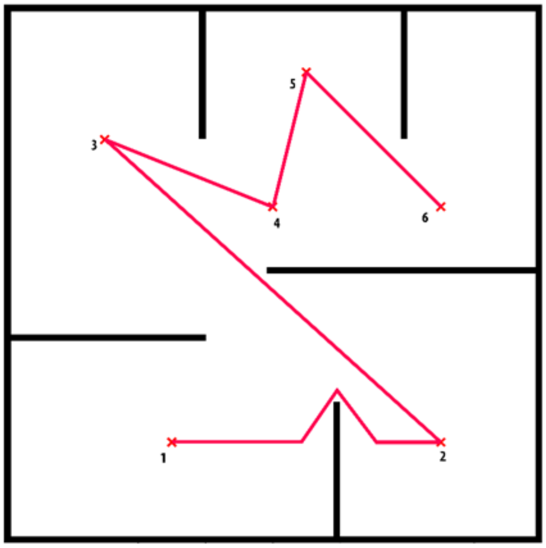


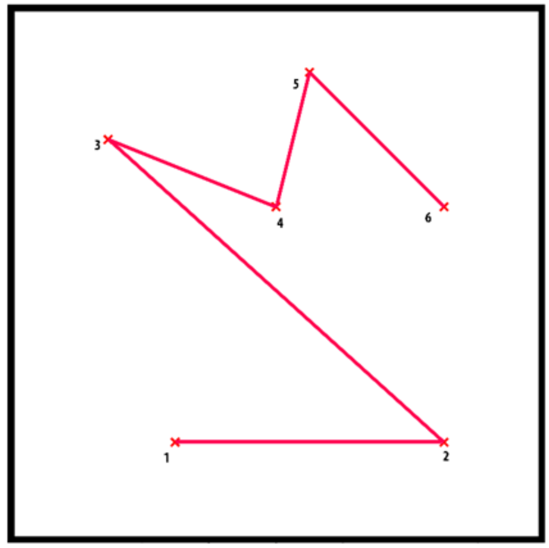
Figure 5. *A non-holonomic swarm robot*

4.1. Problem definition

In this section, the path tracking problem of swarm robots is defined. In the with and without obstacles arena, it is aimed to track the paths depending on the change of the number of robots of the swarm robots and the l_d value determined by the Pure-Pursuit algorithm of the swarm robots. It is aimed for the swarm robots to cooperate in an organized way and follow the path by passing the waypoints placed sequentially on the predetermined path. Swarm robots should be able to move without colliding each other and obstacles during path tracking.



(a)



(b)

Figure 6. *(a)with obstacle and (b)without obstacles arenas for path tracking*

The swarm robots are aimed to follow the path consisting of 6 waypoints placed in a row as shown in Figure 6. The path tracking, which consists of 6 waypoints, is also implemented in with and without obstacle arena shown in Figure 6 (a) and (b). The obstacles have been specially selected to examine how the swarm robots behave on the path created with 6 waypoints.

Swarm robots are asked to follow the path determined from the 1st waypoint to the 6th waypoint in with and without obstacle arena given in Figure 6. In with and without obstacle arena, all of the different number of swarm robots should be able to follow the path starting from the 1st waypoint to the 6th waypoint.

5. Results

In the study, the path tracking process consisting of predetermined sequential waypoints of swarm robots in with and without obstacles arenas is examined. Following the waypoints-based predetermined path, experiments are carried out according to the different number of swarm robots and the l_d value determined by the Pure-Pursuit algorithm used. Experiments include different systematic applications for 3, 5 and 7 robots with 0.3, 0.5 and 1 unit l_d values. Experiments were repeated 50 times. The applied systematic experiments are carried out in with and without obstacles arenas given in Figure 6. Arena sizes are selected as 80 x 80 square units. After the swarm robots have passed 6 determined waypoints, the experiments are ended. The time until the experiments are terminated (number of iterations) measures the performance of the experiment. In the results obtained through systematic experiments, the scalability and flexibility of swarm robots are examined in terms of path tracking behavior.
The systematic experiment results applied for the 0.3 unit l_d value determined in the approach proposed in Figure 7 are shown. Repeated experiments for 0.3 unit l_d value is systematically implemented in with and without obstacles arenas with 3, 5 and 7 swarm robots. The data obtained from the applied systematic experiments are expressed with box plots. The lines in the middle of the box plots show the median value of the completed iteration times of the systematic experiments applied. In systematic experiments applied for 0.3 unit l_d value and 3.5 and 7 robots, the lowest median value was realized with 3 robots in the without obstacles arena as 1360.5 steps and the highest median value was with 7 robots in the with obstacles arena in 2015.5 steps. Considering these values, the experiments carried out in with obstacles arena took longer than those without obstacles. The main reason for this result is that when the swarm robots encounter the obstacle while they follow the path in an organized way, they determine the path both without colliding obstacles and colliding each other. In addition, the distance to the waypoints determined sequentially increases when the robots encounter the obstacle. When the experiments are compared in terms of the number of robots according to the 0.3 unit l_d value, the increase in the number of robots causes an increase in the duration of the experiment.

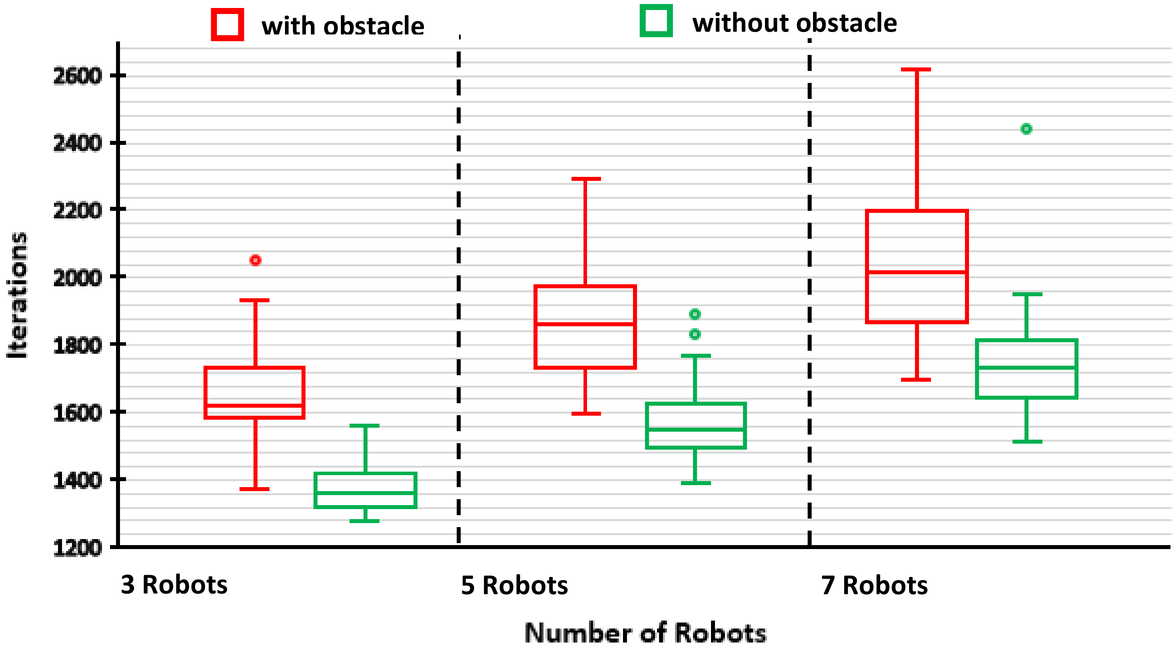


Figure 7. *Systematic test results applied for 0.3 unit l_d value*

Figure 8 shows the systematic test results applied in with and without obstacles arenas for 0.5 l_d value with 3, 5 and 7 robots. In the systematic experiments applied for 3,5 and 7 robots, the lowest median value was realized with 3 robots in the without obstacle arena as 1340.5 steps, and the highest median value was 1885.5 steps with 7 robots in with obstacles arena. According to the results of experiments applied in with and without obstacles arenas, the experiments applied in the disabled arena take longer than the experimental results applied in the without obstacle arena, similar to the results of the experiment applied with a value of 0.3 unit l_d. Similarly, the increase in the number of robots causes an increase in the duration of the experiment. Experimental results applied for 0.5 unit l_d value is obtained at more (wide) time intervals than 0.3 unit l_d value.

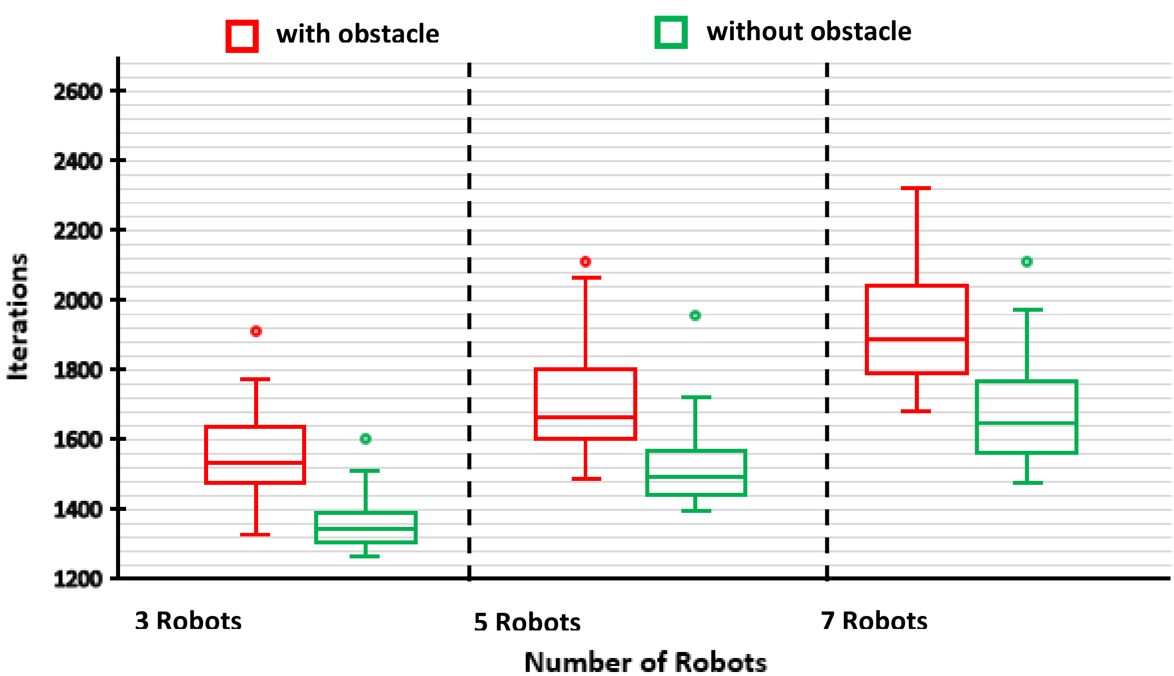


Figure 8. *Systematic test results applied for 0.5 unit l_d value*

Figure 9 shows the systematic test results applied in with and without obstacle arena for 1 unit l_d value with 3, 5 and 7 robots. In the systematic experiments applied for 3,5 and 7 robots, the lowest median value was realized with 3 robots in the without obstacle arena as 1345.5 steps, and the highest median value was 1749.5 steps with 7 robots in with obstacle arena. Similar to the systematic experiments performed with the choice of 0.3 and 0.5 l_d the with obstacle test results lasted longer than the without obstacle test results. In addition, the increase in the number of robots causes an increase in the duration of the experiment. Unlike 0.3 and 0.5 l_d selection in the systematic experiments applied depending on the 1 unit l_d selection, the time intervals for the completion of the experiment are shorter. Due to the increase in l_d value, the decrease in its oscillation in path following does not cause major changes in the duration of the experiment completion. With the oscillation that occurs during path tracking, the collision status of the robots decreases. With this situation, the time for each robot to follow the path without colliding each other decreases.

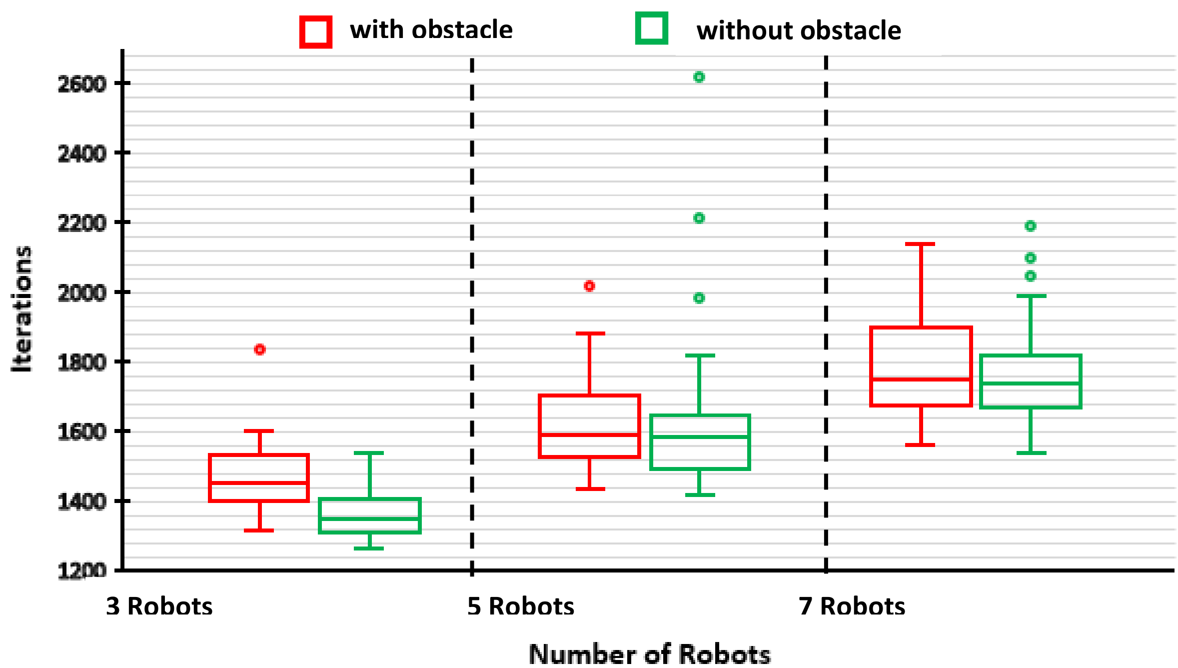
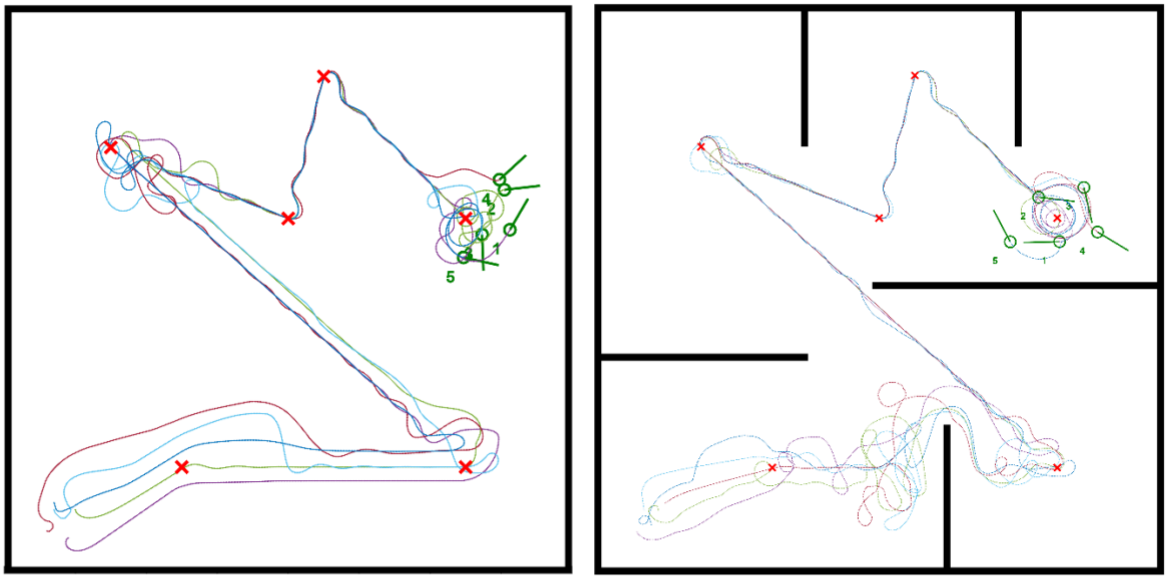


Figure 9. *Systematic test results applied for 1 unit l_d value*

When the applied systematic experiments are evaluated depending on the change of the l_d selection, the time to complete the experiment decreases as the distance l_d increases. When the l_d value increases, collision situations decrease because the swarm robots oscillate less on the desired path.

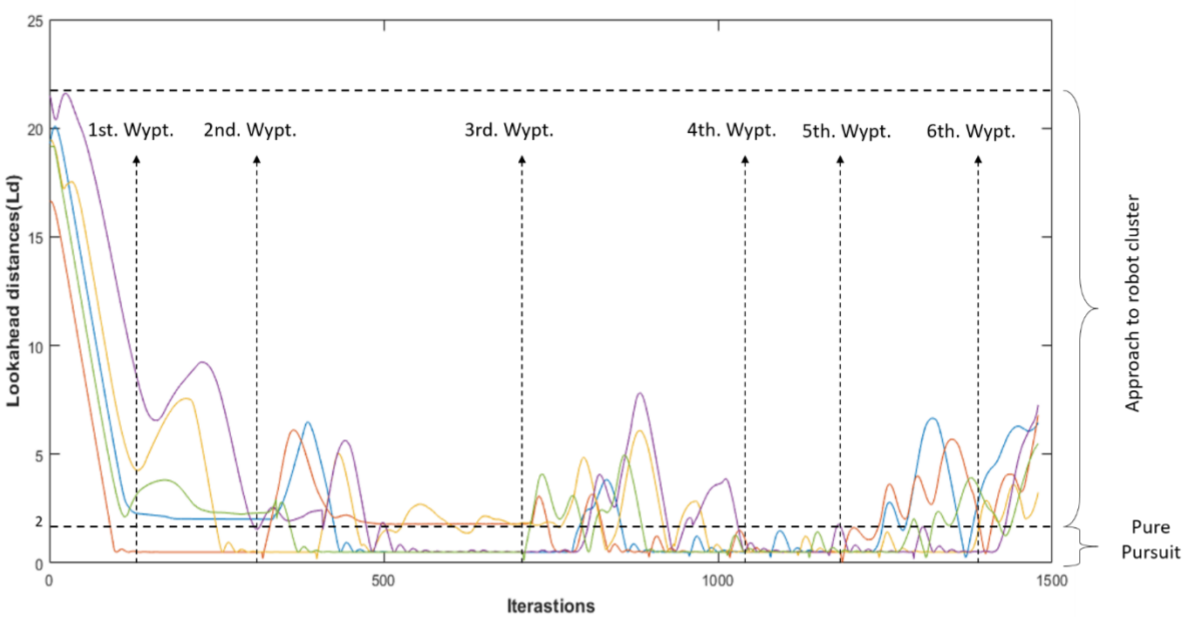
In Figure 10 (a) and (b), 5 swarm robots, whose l_d value is chosen as 0.5 units, and two of the systematic experiments performed in the with and without obstacle arena are shown. In the with and without obstacle experiments, the path trace of each of the swarm robots along the path they follow is shown in Figure 10 (a) and (b). In the systematic experiments applied, the robots are randomly positioned at the beginning of the experiment at the area bounded by 10x10 unit square of 80x80 unit square arena. This determined location is behind the 1st waypoint. In Figure 10 (a) the experiment applied in the without obstacle arena was completed in 1479 iterations. The experiments applied in the without obstacle arena, the swarm robots follow the path determined from the 1st waypoint to the 6th waypoint sequentially. In this experiment, swarm robots move in an organized way without colliding each other on the path with sharp turns. The experiment applied in with obstacle arena in Figure 10 (b) was completed in 1716 iterations. In this experiment, swarm robots are observed both for sharp path turns and how the robots follow when they encounter an obstacle.



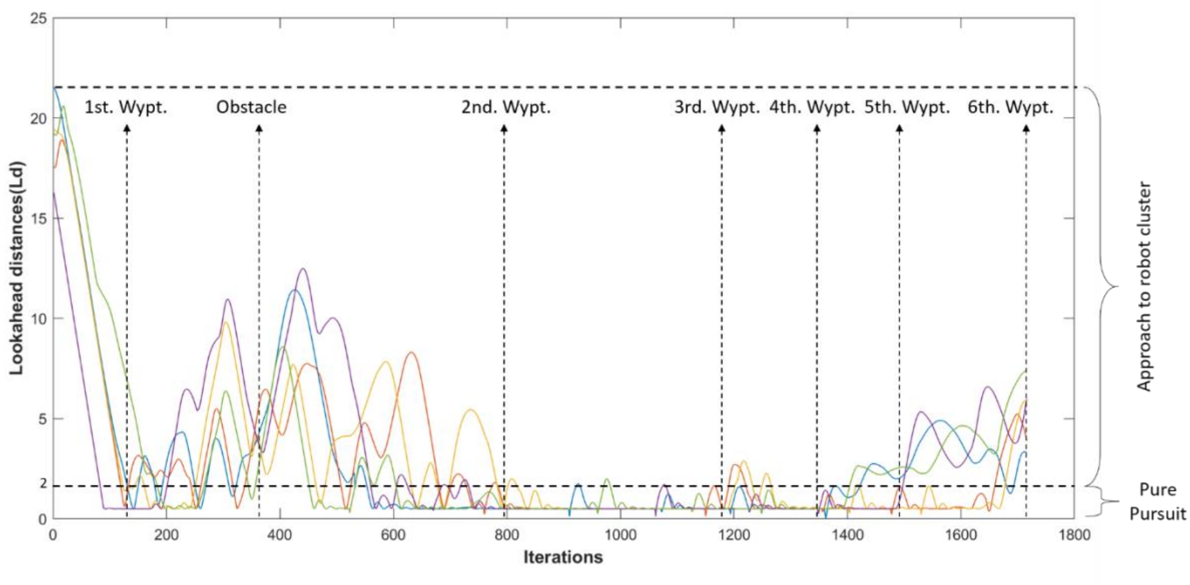
(a) *(b)*

Figure 10. *(a)With and (b)without obstacles arena experiment results for l_d = 0.5 unit*

In Figure 11 (a) and (b) show the values l_d of each of the swarm robots during with and without obstacle path tracking shown in Figure 10. As shown in Figure 11 (a), it shows the conditions for approaching the swarm and applying the Pure-Pursuit algorithm, as indicated in the proposed approach during path tracing of the swarm robots. As in the proposed approach, if the distance of the swarm robots to the path they will follow is over 2 units, it approaches the robots it detects. If it is under 2 units, Pure-Pursuit algorithm is used.



(a)



(b)

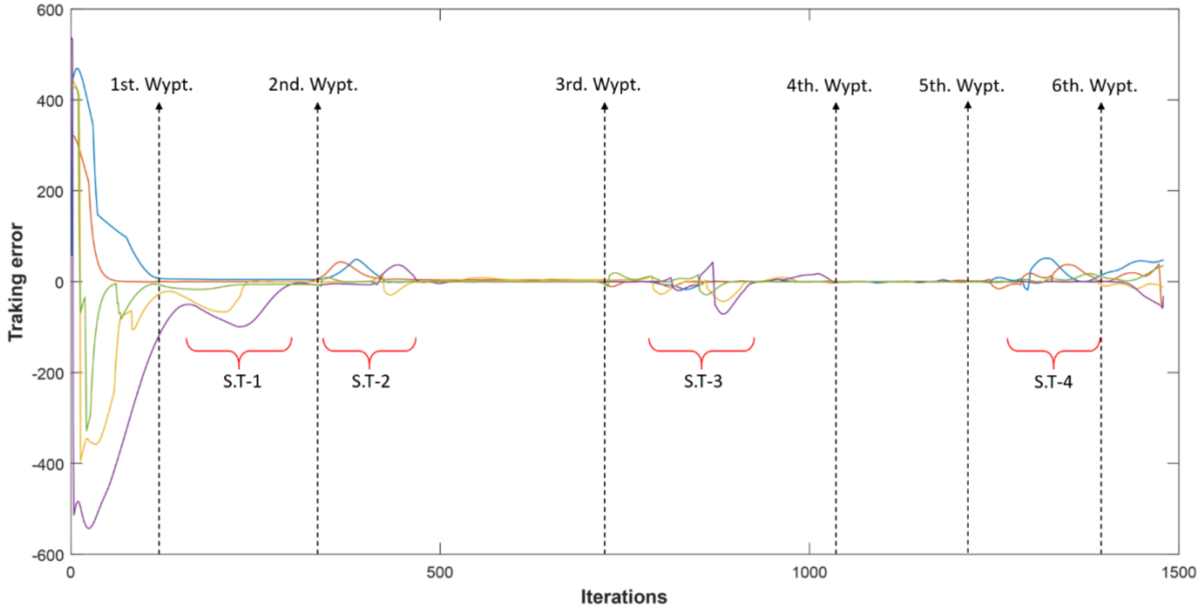
Figure 11. *Lookahead distance test results for l_d = 0.5 unit in (a)with and (b)without obstacles arenas*

In Figure 11 (b), the graph shows the values of l_d from the experiment applied in the arena in Figure 10 (b). In addition, the obstacles that each swarm robot encounters during path tracking and the waypoints they pass through are indicated. When an obstacle or sharp turn encountered by the swarm robots during path tracking, the distance to the determined path increases and this can be seen by looking at the distances l_d . As in the proposed approach, when the l_d value of each of the swarm robots is above 2 units, the robots approach each other in an organized way, and they track the desired path.

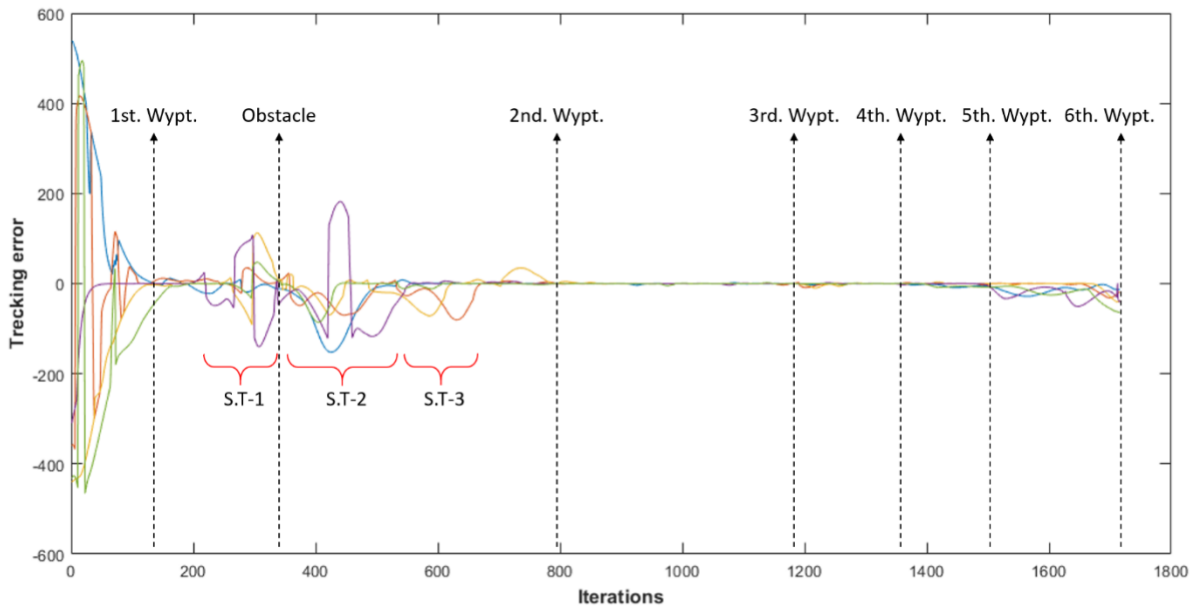
The graphs in Figure 11 show the tracking errors obtained from the experiments performed in with and without obstacle arenas shown in Figure 10. Tracking error, as expressed in equation (9), is the perpendicular distance of the swarm robot to the tracking path.

$$e = \frac{\tan\left(\delta_{pp}(t)\right).l_d{}^2}{2L} \tag{9}$$

As shown in Figures 11 (a) and (b), a tracking error at the time of an obstacle or sharp turn (S.T) is observed as each swarm robot passes through the specified waypoints. The distance of the swarm robots to the path increases to follow when they encounter an obstacle or (S.T). Each swarm robots that are rotating and avoiding obstacles are moving in an organized way to get closer to the path they will follow. In the proposed approach, in the event that swarm robots encounter obstacles, priority is determined to avoid obstacles rather than following the path.



(a)



(b)

Figure 12. *Tracking errors test results for* l_d *= 0.5 unit in (a)with and (b)without obstacles arenas*

6. Conclusion

In this paper, a waypoint-based path tracking approach is recommended for self-organized swarm robots. Each swarm robots act according to the behavior of neighboring robots, which they perceive individually during path tracking. To evaluate the proposed path tracking approach in terms of scalability and flexibility, systematic experiments have been carried out in with and without obstacle arena with different numbers of robots and depending on different lookahead distances. With the proposed approach, each swarm robots exhibit swarm behavior in an organized manner depending on the distance of the lookahead to the path to follow in the with / without obstacle arenas.
According to the proposed approach, robots are not supposed to collide each other and obstacles. This condition affects the time to complete path tracking. In the results obtained from the systematic experiments, it was observed that the path following completion time increases as the number of robots increases.

As observed from the systematic experiments applied in the with obstacle arenas, the completion time of the experiment is extended as the robots escape from the obstacle on the path. According to the results obtained from the systematic experiments, the path following completion time of the swarm robots in with obstacle arena is more than the in without obstacle arena.
Increasing the l_d value also increases the distance to the path that the swarm robot will follow. In this way, the colliding situations of the swarm robots are also reduced. Thus, each swarm robots complete the specified path more quickly. According to the results of the experiment, as l_d value increases, the time for the swarm robots to complete the path tracking decreases.
Using the proposed approach, the results from systematic experiments showed that swarm robots can track path in a flexible and scalable way. Swarm robots also decide under which conditions to apply the Pure-Pursuit algorithm, depending on the neighboring robots they detect, and the individual l_d values.
In future studies, it is aimed to design a path tracking controller according to the dynamic lookahead distance according to the neighboring robots detected by the swarm robots and the surrounding obstacle and collision conditions for path tracking.

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