Fuzzy-based Distributed Behavioural Control with Wall-Following Strategy for Swarm Navigation in Arbitrary-Shaped Environments

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ABSTRACT This paper addresses novel fuzzy-based distributed behavioral control with the wall-following strategy for robot swarm navigation in arbitrary-shaped environments. Instead of avoiding large-size obstacles during the swarm navigation, the proposed distributed control enables the robot swarm to follow obstacle boundaries by transforming from aggregation configuration to one-chain configuration. The wall-following strategy and one-chain configuration empower the swarm navigation to avoid local minima caused by obstacles and connectivity maintenance without dealing with the alignment control of swarm behaviours. The fuzzy-logic control is applied to calculate the parameters of the distributed control strategies. The proposed method is examined and evaluated in both simulation and real experiments.

INDEX TERMS Fuzzy-Logic Control, Distributed Behavioral Control, Robot Swarm Navigation, Wall-Following Strategy, Configuration Transformation, Arbitrary-Shaped Environments, Local Minima.

I. INTRODUCTION

A Swarm of mobile robots can be deployed in several real-world applications, e.g., medical operations, surveillance and monitoring, and search and rescue, thanks to its systematic scalability and applicable flexibility [1], [2]. Ideally, the controller of individual robot should be designed in a simple manner but collective behaviours of the robot swarm should be emergent to perform given tasks. Designing a robot controller for emergent collective behaviours is well recognized as the primary objective in the field of swarm robotics.

Passing through an unstructured and unknown environment is still considered as a critical challenge for the robot Swarm navigation that encounters the key issues: Firstly, Local minima often occur when navigating through large-sized obstacles in both convex and concave shapes, as a result, a robot could easily get trapped in a loop [3] where its control is in equilibrium state leading to disorientation of its motion. Secondly, connectivity maintenance is a critical requirement for collective behaviours [4]–[6], but it leads to the limitation of the robot mobility seen as another kind of local minima [7]. Specifically, when the link quality drops below a desired threshold, robot is required to either stop or move closer to its neighbor until the quality returns to an acceptable level. The more connectivities, the higher mobility restriction [8]. The connectivity maintenance - created local minima often appears with dynamic changes in the environment that affect signal strength measurements as well as anti-flocking situations that robots with the mobility constraint do not move in a common direction. Lastly, the swarm movement is defined as the cohesive and aligned motion of individuals along a common direction. Therefore, how to get the ordered motion to reach the desired destination is another important issue of the robot swarm navigation. Each robot has access to three types of information: relative distance, bearing and orientation of its neighbors. The relative distance and bearing
are required to keep cohesion and avoid collision while the relative orientation is needed for the alignment control in order to synchronize the moving direction. Robots can easily measure themselves the relative distance and bearing by using simple sensors such as infra-red, sonar,... [9], [10]. However, the relative orientation measurement for alignment control requires elaborate sensing capabilities not always available on most robotic platform (e.g. digital compass, communication module...) as well as communication over time-steps between the robots and their neighbors. Alternatively, no-alignment control can be applied to obtain the ordered motion control without requiring relative orientation, but the collective motion in this control type is achieved when most or all robots are informed about the goal direction [11].

This paper considers the cooperative navigation of a robot swarm to pass through the unknown environments with large-sized obstacles in both convex and non-convex forms. Specifically, we propose a comprehensive strategy in which the robot swarm moves in aggregation configuration in obstacle-free environments while moving in one-chain configuration when it encounters large obstacles. The aggregation and one-chain configuration are transformed back and forth by two transition modes, named aggregation to wall-following (A2W) and wall-following to aggregation (W2A). The swarm robots perform wall-following strategy inspired from Bug 2 algorithm [12] while they are in one-chain configuration in order to overcome the large-size obstacles by following their boundary. To be more specific, by using one-chain configuration - an optimal configuration without redundant connectivities, the robot swarm could stably navigates forward using only the obstacle’s boundary without requiring complicated alignment techniques (with continuous communication among swarm robots) as mentioned above. Therefore, our approach focuses on developing a fully distributed control that possibly eliminates the local minima created by the obstacles and the connectivity maintenance constraints. In addition, a fuzzy-logic scheme is used to allows automatic tuning of the parameters of the collective behaviours that helps the proposed control adapt to the changing environment.

The contributions of this paper are claimed as follows:

- We proposed a novel fully distributed control with wall-following strategy for robot swarm navigation only based on the relative distance and bearing measurements of robots themselves without communication. Two swarm configurations and four synthesized controllers are designed to allow the robot swarm to flexibly pass through unknown environment with large-size obstacles.
- We proposed the one-chain configuration with wall-following strategy which solves all three critical issues of swarm navigation in environments with large-sized obstacles as mentioned above. Because the one-chain configuration is an optimal configuration in terms of connectivity links among swarm robots, it minimizes the restriction on each robot’s motion caused by connectivity maintenance, thus, eliminating local minima created by connectivity maintenance. In addition, when the robot swarm navigates using the boundary of large obstacles in one-chain configuration, it eliminates local minima caused by obstacle’s shapes and achieves the ordered motion with only local sensing, without alignment control.

This paper is organized as follows: we discuss related works in section II. Section III presents the preliminaries of robot modelling, control parameter fuzzy units, and connectivity maintenance [8]. The fuzzy-based behavioural architecture for swarm navigation is presented in section IV. Simulations and real experiments are demonstrated and discussed in section V. Finally, we draw conclusions and final remarks in section VI.

II. RELATED WORKS

In passing through an environment with obstacles, if the mobile robots have prior knowledge of the obstacle’s shape, they can plan an effective path to avoid it. Otherwise, moving along the boundary of the obstacle becomes a reasonable strategy to pass the obstacle [13]. From the above view points, the research on issues of the robot swarm movement can be divided into two categories: (1) the collective motion with obstacle avoidance strategies, and (2) the collective motion with wall-following strategies.

In the first category, the flocking algorithm is applied to maintain the ordered motion in a cohesive group of robots and keep safe distance between robots during moving from a source to a destination. Obstacle avoidance algorithm based on potential functions is added to perform obstacle collision avoidance behaviours, mostly small-size obstacles [4], [11]. The ordered motion can be performed by either alignment control which requires the relative orientation of the robot’s neighbours [11] or no-alignment control using wall-following, leader-followers model [4]. The alignment control creates the efficient motion direction synchronization but requires more elaborate sensing mechanisms to obtain the relative orientation of the neighbours while the non-alignment control possibly causes the heading disturbance of robots leading to anti-flocking situations. The situation under connectivity maintenance constraint limits the robot motion. In addition, if only using the flocking algorithm, the robot swarm can face issues such as not being able to deal with the large-sized obstacle, not being able to transform the swarm configuration to pass the narrow passages in the environment, being split into sub-groups leading to member loss as mentioned in [4] if the connectivity maintenance is not considered.

In the second category, instead of the obstacle avoidance behaviours, the wall-following strategy is used to overcome the obstacle by following its boundary. Most research focusing on wall-following strategy was performed on a single robot while very few ones are found in multi-robot systems with challenges in cooperation and interaction between robots [14]–[18]. The swarm configuration in these wall-
The formation detect the obstacle in front of them. In [16], if more than whole formation is considered as encountering the obstacle moving direction and keeping the formation of robots. The activates the wall-following strategy with synchronizing the determine the presence of the large convex-obstacles and [15], the robot swarm uses communication to cooperatively obstacle-created local minima with pure rolling motion. In [14], the authors considers the cooperation of a four-robots swarm based on communication for moving in formations. If there is no space for robots to stand side-by-side, robots move sequentially with wall-following strategy while they move side-by-side in a row if there is enough space between them. The communication is used to make consensus actions in the swarm such as stop, delay, turn left, forward,... In [17], the wall-following control of multi-robot systems is considered in the scenario of walls formed in the shape of polygons with convex and non-convex corners. The leader-follower model is used in which the leader performs the wall-following strategy of a single robot and followers follow the leader by tracking it as a moving target. The obstacle avoidance algorithm is added to allow the follower to avoid the coming collision with the wall first instead of continuing to follow the leader. The control strategy uses only local sensing the relative distance and bearing measured by infrared sensors and tested with two robots. In [18], the robot swarm moves from

| Problems addressed | Motion strategy when encountering obstacles | Swarm configuration transition | Control Parameters | Maintaining connectivity | Eliminating local minima | Distributed control |
|--------------------|---------------------------------------------|-------------------------------|-------------------|--------------------------|--------------------------|-----------------------|
| [4]               | Moving from source to destination along a pre-planned path | Obstacle avoidance | NO | Pre-defined | YES | Small-size, Convex | No consider | YES |
| [11]              | Collective motion with alignment control based on communication | Obstacle avoidance | NO | Pre-defined | NO | Small-size, Convex | No consider | NO |
| [14]              | Moving from source to destination with passing non-convex large-size obstacles | Wall-following with pure rolling motion in vortex pattern | YES, with communication | Pre-defined | NO | Large-size, non-convex | No consider | NO |
| [15]              | Moving from source to destination with keeping formation | Wall-following with keeping formation | NO | Pre-defined | NO | Large-size, Convex | No consider | NO |
| [16]              | Cooperation of a robot swarm based on communication for moving in parallel and serial formations | Wall-following with one-chain configuration | YES, with communication | Automatically tuned by fuzzy-logic scheme | NO | Large-size, Convex and non-convex | No consider | NO |
| [17]              | Wall-following control | Wall-following with one-chain configuration | NO | PD controller | No consider | No consider | YES |
| [18]              | Moving from source to destination with changing between triangular and line formations to overcome obstacles | Wall-following with one-chain configuration | YES, with communication | Pre-defined | NO | Large-size, Convex and non-convex | No consider | NO |
| Our strategy      | Moving from source to destination with changing between flocking and one-chain configuration to overcome obstacles | Wall-following with one-chain configuration | YES, without communication | Automatically tuned by fuzzy-logic scheme | YES | Large-size, Convex and non-convex | YES | YES |
a source to destination in a formation (such as diamond) with leader-follower flocking control. If the formation encounters the obstacle that prevents the robots from maintaining their formation, the formation is transformed into a line formation for wall-following strategy. This situation is identified in two cases: the leader suddenly receives a huge repulsive force from both sides of the forward direction, or one of the robots in the boundary of the formation receives a huge repulsive force from one direction. The reinforcement learning is adopted to implement the robot behavioral selection from a set of behaviors including goal approaching, obstacle avoidance, collision avoidance, wall-following movement through predicting abilities of the robot during motion. In these few existing studies, most studies is not distributed control requiring communication for configuration transition as well as configuration maintenance [14]–[16], [18], excepts [17] that only considers the wall-following control without configuration transition.

Table 1 summarizes the differences between our proposed approach and the previously reviewed works. To the best of our knowledge, our comprehensive solution is the first fully distributed control with wall-following strategy for swarm navigation in unknown-obstacle environments. It allows to transform the swarm configuration from aggregation to one-chain and vice versa without requiring communication. The proposed control ensures the connectivity maintenance of the robot swarm as well as solves local minima problem derived from both the large-size obstacle and the connectivity maintenance. In addition, the fuzzy - logic scheme for automatic tuning of the control parameters helps the robot swarm adapt to the changing environment.

### III. PRELIMINARIES

#### A. ROBOT MODELLING

The robot swarm consists of $N$ differential drive mobile robots in two dimensional (2D) space. Because the current-technology sensor could not meet the requirements for long-range wall following (within 5cm) as explained in [19], [20], we assume that we have a tactile sensor (TS) as a proximity sensor on robot $i$. This sensor has proximity sensing radius of $r_s$ and is responsible for precisely detecting object boundary in proximity for wall-following. In addition, robot $i$ also has a long-range sensor (LRS) for detecting object within a longer sensing range $r_L$, $r_s \ll r_L$. Both sensors are modeled by the shape of discs Fig. 1. Let $i(x_i, y_i)$ be the robot $i$’s position in 2D space. Robots within $r_L$ distance towards robot $i$ are considered as neighbor robots of robot $i$. $N_i$ is a set of neighbors of robot $i$.

#### B. CONTROL PARAMETER FUZZY UNITS

The concept of fuzzy logic was introduced by Zadeh [21] and has become a means of treating uncertain and imprecise sensor’s information using linguistic rules. In this paper, fuzzy logic is used to design five control parameters for five different individual behaviors (including move-along-the-wall, wall-push, wall-pull, cohesion, separation). Each control parameter fuzzy unit has four steps as follows:

- First, the fuzzification step maps tactile sensor and long-range sensor readings to corresponding sensor partitions using input membership functions (MFs) as in Fig. 1. The TS sensing area is divided into more partitions than the LRS in order to increase the control resolution at the short distance. The relative distance $d_{i,wp}$ and bearing $\theta_{i,wp}$ readings of TS are mapped to corresponding sensor partitions using input MFs in Fig. 2(a) and (b). Similarly, $d_{i,j}$ and $\theta_{i,j}$ of LRS are mapped using input MFs in Fig. 2(c) and (d). Fuzzy antecedent variable of $d_{i,wp}$ and $d_{i,j}$ are evaluated with the fuzzy sub-sets of Near, Med (Medium), Far, whereas $\theta_{i,wp}$ and $\theta_{i,j}$ are evaluated with the fuzzy sub-sets of FL (Front Left), L (Left), B (Back), R (Right), FR (Front Right) as shown in Fig. 2(c) and (d).

- Then, a set of If-then rules or the rule base for each behavior is designed as in Table 2 and 3 to define the relationships between input and output membership functions. The output variables $\alpha, \beta, \gamma, \nu, \tau$ subject to the Z (Zero), S (Small), M (Medium), B (Big), VB (Very Big) singleton membership functions shown in Fig. 3.

- The fuzzy inference step calculates the degree of fulfillment (DOF) for each rule and the output membership functions (depicted in Fig. 3) are truncated at DOF level. This study uses Mamdani fuzzy inference system, rule connection “and” method, “min” for the “and” method. The final output membership function is the synthesis of all the individual output membership functions using OR operator.

- In the last step, the “Center of Area” method is used for defuzzification translating the linguistic value to crisp values.

#### C. CONNECTIVITY MAINTENANCE

Connectivity maintenance based on mobility constraint in [8] is applied for every robot $i$ as the bounded condition which guarantees the integrity preservation of the robot swarm without loss of members as well as the information...
Table 2. Rule base for change of $\alpha$ and $\beta$ (using readings of TS)

| $d_i^{TS}$ / $\theta_i^{TS}$ | FL | L | R | FR |
|----------------------------|----|---|---|----|
| Near                      | Z  | B | Z | VB |
| Medium                    | Z  | B | Z | VB |
| Far                       | B  | Z | B | B  |

Table 3. Rule base for change of $\gamma$, $\nu$, and $\tau$ (using readings of LRS)

| $r_i^{LRS}$ / $\phi_i^{LRS}$ | FL | Back | FR |
|------------------------------|----|------|----|
| Near                        | Z  | Z    | B  |
| Medium                      | Z  | M    | Z  |
| Far                         | S  | Z    | S  |

The core concept of our paper is to design a control for swarm robots to reach a given target point or a set of target points in unknown environments with large-sized obstacles. To do so, a fuzzy-based wall following method is designed including two main elements: control parameter fuzzy units (described in III-B) and synthesized controllers as in Fig. 4.

We used different synthesized controllers to generate different desired swarm behaviors: wall-following strategy (WF), aggregation strategy, aggregation-to-wall-following mode (A2W) and wall-following-to aggregation mode (W2A). Synthesized controllers are the combination of following individual behaviors: move-along-the-wall, wall-push, wall-pull, cohesion, separation, move-to-goal, random-walk and move-to-wall. The switching algorithm 1 helps a robot switch among synthesized controllers in order for the robot swarm to transform into one-chain configuration to avoid local minima caused by competing potentials and connectivity constraints.

IV. FUZZY-BASED DISTRIBUTED BEHAVIOURAL CONTROLLER

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A. WALL-FOLLOWING STRATEGY

The wall-following strategy is considered as a novel approach enabling the robot swarm to pass large obstacles by following its boundary. This strategy is synthesized by wall-pushing \( \vec{v}_{i}^{wps} \), wall-pulling \( \vec{v}_{i}^{wp} \), and move-along-the-wall \( \vec{v}_{i}^{matw} \) behaviors; this strategy is activated when the distance between robot \( i \) and boundary of obstacle is within the tactile sensing range, \( r_{S} \) and the obstacle blocks the line of sight (LoS) connecting robot \( i \) and its given target point.

\[
\vec{V}_{WF} = \vec{v}_{i}^{matw} + \vec{v}_{i}^{wps} + \vec{v}_{i}^{wp} \tag{1}
\]

1) Move-along-the-wall behavior

This behavior drives robot \( i \) along the boundary of the obstacle and maintains a constant distance with its closest neighbor robot in the front. Assume \( W \) is the set of finite points on the boundary and the coordinate of the closest point detected by the tactile sensor of robot \( i \) is \( w_{i}^{TS} (x_{wp}^{TS}, y_{wp}^{TS}) \) (\( w_{i}^{TS} \in W \)), we have:

\[
\vec{v}_{i}^{matw} = \gamma \begin{bmatrix} (y_{uwp} - y_{i}) \\ (x_{uwp} - x_{i}) \end{bmatrix} \tag{2}
\]

\( \gamma \) fuzzy unit is used to control the parameter \( \gamma \) for this behavior. \( \gamma \) is determined for the input antecedent variables \( d_{i,j}^{LRS} \) and \( \theta_{i,j}^{LRS} \) using rules in Table 2, and subjects to output MFs in Fig. 3 (a). \( d_{i}^{TS} \) and \( \theta_{i}^{TS} \) are the relative distance and angle towards the closest point on the boundary of the obstacle \( w_{i}^{TS}, \) respectively.

2) Wall-pushing behavior

This behavior makes robot \( i \) not to collide with the wall while performing wall-following strategy.

\[
\vec{v}_{i}^{wps} = \beta \begin{bmatrix} (x_{i} - x_{wp}^{TS}) \\ (y_{i} - y_{wp}) \end{bmatrix} \tag{3}
\]

The control parameter \( \beta \) of this behavior is computed by \( \beta \) fuzzy unit. \( \beta \) is determined for the input antecedent variables \( d_{i,wp}^{TS} \) and \( \theta_{i,wp}^{TS} \) using rules in Table 2, and subjects to output MFs in Fig. 3 (a).

3) Wall-pull behavior

Together with the wall-pushing behaviour, a wall-pull behaviour ensures robot \( i \) to maintain a certain distance to the wall when performing the wall-following strategy.

\[
\vec{v}_{i}^{wp} = \alpha \begin{bmatrix} (x_{i}^{TS} - x_{j}) \\ (y_{wp} - y_{i}) \end{bmatrix} \tag{4}
\]

The control parameter \( \alpha \) is calculated by \( \alpha \) fuzzy unit. \( \alpha \) is determined for the input antecedent variables \( d_{i,wp}^{TS} \) and \( \theta_{i,wp}^{TS} \) using rules in Table 2, and subjects to output MFs in Fig. 3 (a).

B. AGGREGATION STRATEGY

Beside the wall-following strategy, the aggregation strategy is designed to guide the robot swarm to navigate toward its target in an obstacle-free environment. This strategy is synthesized by cohesion \( \vec{v}_{i}^{c} \), separation \( \vec{v}_{i}^{s} \), and move-to-goal \( \vec{v}_{i}^{mtg} \) behaviours which are activated when the distance between the robot and boundary of obstacles is outside the LRS range (\( r_{L} \)). The emergent behaviour of robot \( i \) is represented by:

\[
\vec{V}_{A} = \vec{v}_{i}^{c} + \vec{v}_{i}^{s} + \vec{v}_{i}^{mtg} \tag{5}
\]

1) Cohesion behavior

This behaviour is considered as the attraction force applied for robot \( i \) and \( j \) to get closer if \( j \in N_{i} \setminus N_{i}^{near} \), where \( N_{i}^{near} \) is a set of robot \( i \)'s neighbours in the LRS-near sensing area.

\[
\vec{v}_{i}^{c} = \sum_{j \in N_{i} \setminus N_{i}^{near}} \nu_{ij} \begin{bmatrix} (x_{j} - x_{i}) \\ (y_{j} - y_{i}) \end{bmatrix} \tag{6}
\]
where $\nu_{ij}$ is the control parameter corresponding to robot $i$ and its neighbouring robot $j \in N_i \setminus N_{i \text{near}}$.

The control parameter $\nu_{ij}$ is governed by $\nu$ fuzzy unit. $\nu_{ij}$ is determined for the input antecedent variables $d^L_{i,j} LRS$ and $\theta_{i,j} LRS$ using rules in Table 3, and subjects to output MFs in Fig. 3 (c). $d^L_{i,j} LRS$ and $\theta_{i,j} LRS$ are the relative distance and angle towards neighbouring robots $j \in N_i$, respectively.

2) Separation behavior
In oppose to the cohesion behaviour, this behaviour drives a robot away from nearby robot $j$ to avoid collision, $j \in N_i \setminus N_{i \text{far}}$, where $N_{i \text{far}}$ is a set of robot $i$’s neighbors in LRS-far sensing area.

$$\vec{v}_i^s = \sum_{j \in N_{i \text{far}} \setminus N_i} \tau_{ij} \left[ \begin{array}{c} (x_i - x_j) \\ (y_i - y_j) \end{array} \right]$$ (7)

where $\tau_j$ is the control parameter corresponding to robot $i$ and its neighbouring robot $j \in N_i \setminus N_{i \text{far}}$.

$\tau$ fuzzy unit is used to calculate the control parameter $\tau_{ij}$ for this behavior. $\tau_{ij}$ is determined for the input antecedent variables $d^L_{i,j} LRS$ and $\theta_{i,j} LRS$ using rules in Table 3, and subjects to output MFs in Fig. 3 (c).

3) Move-to-goal behavior
This behavior is the driven factor making robot $i$ achieve its target by pushing it toward the goal position $g(x_{g}, y_{g})$.

$$\vec{v}_i^{mtg} = \left[ \begin{array}{c} (x_{g} - x_i) \\ (y_{g} - y_i) \end{array} \right]$$ (8)

C. TRANSITION MODES
The wall-following and aggregation strategies are the synthesized controllers enabling swarm navigation in the desired one-chain and aggregation configurations, respectively. However, these strategies are only effective if the robot swarm has been in such swarm configurations. Therefore, to ensure successful transition between two configurations, two synthesized controllers of the transition modes created.

1) Aggregation to Wall-Following (A2W mode)
The purpose of this mode is to force the transition from aggregation to one-chain configuration. Move-to-wall behavior ($\vec{v}_i^{mtw}$) is created to drive robot $i$ closer to boundary of obstacles until the wall-following strategy is activated.

$$\vec{v}_i^{mtw} = \left[ \begin{array}{c} x_{i}^{LRS} - x_i \\ y_{i}^{LRS} - y_i \end{array} \right]$$ (9)

where the coordinate of the closest point on the obstacle’s boundary detected by the LRS of robot $i$ is $w_{LRS} x_{i}^{LRS}, y_{i}^{LRS}$, where $w_{LRS} \in W$ and $r_s < \left\| w_{LRS} \right\| \leq r_L$.

Together with swarm cohesion and separation, there are three individual behaviours incorporated in the mode as shown in Fig. 4. As a result, the aggregation configuration gradually transforms into one-chain configuration while performing collision avoidance. This transition mode is activated when LRS of robot $i$ detects an obstacle blocking the LoS and deactivated when the wall-following strategy is activated. The behaviour vector for robot $i$ in A2W mode is given by:

$$\vec{V}_{A2W} = \vec{v}_i^{mtw} + \vec{v}_i^c + \vec{v}_i^s$$ (10)

2) Wall-following to Aggregation (W2A mode)
In oppose to A2W mode, this transition mode is created to ensure the transition from one-chain to aggregation configuration. Due to the blocked LoS between immediate neighbouring robots, the swarm remains in one-chain configuration when most of robots exit the wall-following strategy. Random-walk behavior $\vec{v}_i^{rw}$ is activated when robots moving out from the wall. $\vec{v}_i^{rw}$ acts the main factor to create geometric chaos for aggregation configuration to form and is defined as a perpendicular vector to the line connecting two neighbour robots $(j, k \in N_i)$.

$$\vec{v}_i^{rw} = \left[ \pm (y_k - y_j) \right] \pm (x_k - x_j)$$ (11)

where the sign $\pm$ is determined by probability 50% of selecting $+$ or $-$.

The W2A mode is activated when the LRS of robot $i$ escaping the wall-following strategy still observes the obstacle which does not block the LoS and deactivated when there is no obstacle within $r_L$. The further the swarm moves away from the obstacle, the more number of robots turn into aggregation configuration. The behaviour vector for robot $i$ is given by:

$$\vec{V}_{W2A} = \vec{v}_i^{rw} + \vec{v}_i^c + \vec{v}_i^s + \vec{v}_i^{mtg}$$ (12)

Along with swarm cohesion, separation and move-to-goal behaviours, the robot swarm moves toward the goal as a whole while each robot avoids collision with its neighbours during the transition mode. All the robots automatically change to the aggregation strategy when they are no longer observing the obstacle within the LRS range.

D. A LOCAL MINIMA-FREE APPROACH
Local minima, which is always a problem for robot navigation, happens when the sum of the attractive force and repulsive force is equal to zero. Specifically, researchers in [3], [22] pointed out that local minima appears in environments with concave obstacles, large obstacles, narrow channels. Moreover, in a swarm robot system, we must add the collision avoidance among robots, therefore, the system is more prone to local minima.

In our proposed method, there are two states that the robots could fall into local minima (when swarm robots interact with obstacles): 1. when the robots approach the obstacle and 2. when the robots contour the obstacle’s boundary. However, local minima in these two states could be avoided by using two proposed synthesized controllers: aggregation-to-wall-following mode and wall-following strategy, respectively.

In wall-following strategy, while the wall-pushing vector and wall-pulling vector are collinear and in opposite direction, the move-along-the-wall vector is in perpendicular...
direction with the above two vector. Therefore, the sum of those vectors are not equal zero and the robot always keeps moving unless the robot has to wait for its frontal robots to move forward to avoid collision ($\gamma = 0$).

In aggregation-to-wall-following mode, the sum of all vectors could easily be zero and the robot motion stops. However, this stop motion is designed for a robot to avoid collision with frontal robots. In Fig. 5(a), when robot $i$ gets too close to robot $j$, the magnitude of separation vector outweighs cohesion vectors and equals to move-to-wall vector. Despite the sum of vectors is zero, the situation is not considered as local minima of motion. Because the frontal robot $j$ is either in A2W mode or WF strategy, robot $j$ will keep moving closer to the obstacle or along the wall, as a result, make room for robot $i$ approach the wall.

V. EXPERIMENT RESULTS AND DISCUSSION

We present the results of the simulation and real experiment in the environment consisting of both convex and non-convex obstacles, and evaluate the performance of the proposed control architecture.

A. EXPERIMENT SETUP

In the simulation and real experiment, we used differential drive mobile robots which are identical and in square shapes with the side 10 cm. The maximum speed of all the robots was set at $u_{\text{max}} = 0.3 \text{m/s}$. The TS range was set at 5 cm and the LRS range was set at 70 cm. The mission of the swarm is to reach a given target point or a set of target points.

The simulation with 15 robots was implemented in the scenario $22 \text{m} \times 9 \text{m}$ containing one convex large obstacle and two concave large obstacles arranged randomly in order to obstruct the swarm navigation to reach the destination as depicted in Fig. 6. The real experiment was carried out with six robots in the arena of $4 \text{m} \times 3 \text{m}$ with one concave large obstacle as illustrated in Fig. 8. A motion-tracking system was used to reduce difficulties of representing sensing and connectivity of the robots. At the initial stage, all the robots were in the aggregation strategy and they could not observe such obstacles.

B. ENTROPY

To evaluate the efficiency in transforming between two swarm configurations, we measured the positional disorder of the swarm using a metric named entropy. A drop in entropy value indicates an aggregation happening while an increase shows that the swarm is transforming toward a more scattered configuration. It is calculated by finding clusters within the swarm. Robot $i$ and robot $j$ are considered to be in the same cluster if $|j - i| \leq h$, where $i$ and $j$ denote the position vectors of robot $i$ and robot $j$ respectively. Shannon’s information entropy $H$ of a cluster is defined as:

$$H(h) = \sum_{z=1}^{M} p_z \log_2 p_z$$

where $p_z$ is the proportion of the individuals in the $z^{th}$ cluster and $M$ is the number of clusters.

Entropy values are integrated over a range from 0 to $\infty$ of $h$ to find the total entropy $S$:

$$S = \int_{0}^{\infty} H(h) dh$$

C. RESULTS AND DISCUSSION

In the simulation\(^1\), we examined how the distributed control guided a robot to navigate through convex and concave obstacles as demonstrated in Fig. 6. All the robots were in the aggregation configuration (Fig. 6.A) and they did not observe obstacle at the initial stage. Initially, the robot used the aggregation strategy (Eq. 5) to navigate toward the goal. As the robot came closer to the goal and detected obstacle 1 (Fig.6(a)) obstructing the LoS using LRS, it switched to aggregation-to-wall following mode (Eq. 10). As a result, the robot came closer to the obstacle and eventually the obstacle was within the TS sensing range. When the robots detected obstacles using TS, the wall-following strategy (Eq. 1) was activated to guide the robot swarm to move along the obstacle boundary to get to the other side of the obstacle. The wall-following-to-aggregation mode (Eq. 12) was activated when the robot started exiting the obstacle boundary (Fig. 6.C) to create geometric chaos for aggregation configuration to form. Finally, the robot switched back to the aggregation strategy when it no longer observed the obstacle within the LRS range. Similarly, when the robots encountered obstacle 2 and 3, appropriate synthesized controller will be selected on each robot using algorithm 1 and the swarm configurations were transformed from aggregation to one-chain configurations and vice versa through the transition modes. In addition, all the control parameters of each strategy or mode are automatically tuned by using our control parameter fuzzy units in III-B.

To evaluate the effectiveness of synthesized controllers in swarm configuration transformation, we analyze the correlation of the number of robot in different modes and the entropy value in Fig. 7. To give readers a better understanding of Fig. 7, we examined a snapshot at time-step 2500\(^{th}\) of this combined chart. At step 2500\(^{th}\), when the robot swarm was approaching the obstacles, there were 4 robots

\(^1\)Simulation: https://youtu.be/L75EBAfDvVM
in Aggregation strategy (grey bar), 4 robots in aggregation-to-wall-following mode (orange bar) and 7 robots in wall-following strategy (cyan bar). To overcome obstacles, all robots had to consecutively operate in aggregation-to-wall-following mode, wall-following strategy, and wall-following-to-aggregation mode. Considering the obstacle 1 in Fig.6(a), when the robot swarm approached and then followed the obstacle’s boundary as in Fig.6 snapshot B, robots gradually switched into A2W mode and then WF strategy. As the number of robots in WF strategy increased from 0 to 15, the entropy also increases from 0.05 to 1 (see the first peak of entropy in Fig. 7). This increase in entropy value indicates the swarm was transforming toward a scattered configuration, and eventually, the one-chain configuration. On the other hand, when the swarm was exiting the obstacle, the majority gradually switched to W2A mode and then aggregation strategy as depicted in Fig.6 snapshot C. As a result, the entropy decreased from 1 back to 0.05; which indicates the swarm robots were aggregating into a more cohesive configuration. The same pattern could be observed when the robot swarm encountered obstacles 2 and 3, which show the adaptability of our approach to different environments. In addition, while researchers in [14]–[18] allowed swarm robots to communicate to synchronize controller or behavior switching. Fig. 7 shows that multi synthesized controllers or states coexisted and independent at each time step. This confirmed the fully distributed attribute of our control.

We witnessed that the robot swarm successfully navigated toward the desired destination without the appearance of local minima caused by obstacles and connectivity maintenance thanks to the distributed control shown in Fig. 4. To overcome a large obstacle, any robot of the swarm must consecutively operate in A2W mode, WF strategy, and W2A mode. At the WF strategy, each robot must follow the boundary of the obstacle, hence, the robot swarm could overcome any local minima caused by obstacle of any shapes. Not only contouring the obstacle boundary, each robot also maintained the cohesion with its frontal robot. As a result, a one-chain configuration with minimum number of connectivities is formed during WF strategy (e.g. only 14 connectivities in Fig. 6, G) helping the robot swarm avoid any local minima caused by connectivity constraints while avoiding obstacles without experiencing member loss.

We also conducted the real experiment\(^2\) with the swarm of six mobile robots passing a concave obstacle as shown in Fig. 8. Similar to simulation, the swarm was successfully transformed from the aggregation to one-chain configuration when following the obstacle boundary and switched back to the aggregation when they pass over the obstacle. On the contrary, when we applied a simple flocking algorithm which only has three basic behavior: alignment, separation and cohesion to overcome large-sized obstacles, the swarm failed to overcome all three obstacles.

**VI. CONCLUSION**

In this paper, we addressed the fuzzy-based distributed behavioural control with the wall-following strategy. We demonstrated that the novel distributed control enabled the robot swarm to navigate through arbitrary-shaped environments by switching back and forth between two swarm configurations using different synthesized controllers. Using the one-chain configuration together with wall-following strategy, we proved that no local minima caused by either obstacles or connectivity maintenance appeared during the swarm navigation in both the simulation and the real exper-

\(^2\)Real experiment: https://youtu.be/NLSUcJrdHdk
iment. Moreover, all the control parameters of each synthesized controller are automatically tuned by using our control parameter fuzzy units. In the future, we aim to examine aspects of layered wall-following strategy as well as active tactile-based swarming behaviours.

REFERENCES

[1] E. Sahin, “Swarm robotics: From sources of inspiration to domains of application.” in International workshop on swarm robotics. Springer, 2004, pp. 10–20.

[2] M. Schranz, M. Umlauf, M. Sende, and W. Elmenreich, “Swarm robotic behaviors and current applications,” Frontiers in Robotics and AI, vol. 7, apr 2020.

[3] F. Matoui, B. Boussaid, and M. N. Abdelkrim, “Local minimum solution for the potential field method in multiple robot motion planning task,” in 2015 16th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA). IEEE, 2015, pp. 452–457.

[4] H. Zhao, H. Liu, Y.-W. Leung, and X. Chu, “Self-adaptive collective motion of swarm robots,” IEEE Transactions on Automation Science and Engineering, vol. 15, no. 4, pp. 1533–1545, 2018.

[5] W. Kowalczyk, “Formation control and distributed goal assignment for multi-agent non-holonomic systems,” Applied Sciences, vol. 9, no. 7, p. 1311, 2019.

[6] A. Benzerrouk, L. Adouane, and P. Martinet, “Stable navigation in formation for a multi-robot system based on a constrained virtual structure,” Robotics and Autonomous Systems, vol. 62, no. 12, pp. 1806–1815, 2014.

[7] M. A. Hsieh, A. Cowley, V. Kumar, and C. J. Taylor, “Maintaining network connectivity and performance in robot teams,” Journal of field robotics, vol. 25, no. 1-2, pp. 111–131, 2008.

[8] P. D. Hung, T. Q. Vinh, and T. D. Ngo, “Hierarchical distributed control for global network integrity preservation in multirobot systems,” IEEE transactions on cybernetics, vol. 50, no. 3, pp. 1278–1291, 2019.

[9] W. M. Spears, W. M. Spears, D. F. Spears, J. C. Hamann, and R. Heil, “Distributed, physics-based control of swarms of vehicles,” Autonomous Robots, vol. 17, pp. 137–162, 2004.

[10] J. Pugh, X. Raemy, C. Favre, R. Falconi, and A. Martinoli, “A fast onboard relative positioning module for multirobot systems,” IEEE/ASME Transactions on Mechatronics, vol. 14, pp. 151–162, 2009.

[11] E. Ferrante, A. E. Turgut, A. Stranieri, C. Pincirolli, M. Birattari, and M. Dorigo, “A self-adaptive communication strategy for flocking in stationary and non-stationary environments,” Natural Computing, vol. 13, no. 2, pp. 225–245, 2014.

[12] V. Lumelsky and A. Stepanov, “Dynamic path planning for a mobile automation with limited information on the environment,” IEEE transactions on Automatic control, vol. 31, no. 11, pp. 1058–1063, 1986.

[13] P. van Turennout, G. Honderd, and L. van Schelven, “Wall-following control of a mobile robot,” in Proceedings 1992 IEEE International Conference on Robotics and Automation, 1992, pp. 280–285 vol.1.

[14] M. H. Mabrouk and C. R. McInnes, “An emergent wall following behaviour to escape local minima for swarms of agents,” International Journal of Computer Science, vol. 35, no. 4, pp. IJS–35, 2008.

[15] D. Xu, X. Zhang, Z. Zhu, C. Chen, and P. Yang, “Behavior-based formation control of swarm robots,” mathematical Problems in Engineering, vol. 2014, 2014.

[16] A. N. Jati, R. E. Saputra, M. G. Nurcahyadi, and N. T. Al Ghifari, “A multi-robot system coordination design and analysis on wall follower robot group.” International Journal of Electrical & Computer Engineering (2088-8708), vol. 8, no. 6, 2018.

[17] K. Zhu, C. Cheng, C. Wang, and F. Zhang, “Wall-following control of multi-robot based on moving target tracking and obstacle avoidance,” in International Conference on Cognitive Systems and Signal Processing. Springer, 2018, pp. 534–541.

[18] M. Wang, B. Zeng, and Q. Wang, “Research on motion planning based on flocking control and reinforcement learning for multi-robot systems,” Machines, vol. 9, no. 4, p. 77, 2021.

[19] D. Jung and A. Zelinsky, “Whisker based mobile robot navigation,” in Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems. IROS’96, vol. 2. IEEE, 1996, pp. 497–504.

[20] Y. Ando and S. Yuta, “Following a wall by an autonomous mobile robot with a sonar-ring,” in Proceedings of 1995 IEEE International Conference on Robotics and Automation, vol. 3. IEEE, 1995, pp. 2599–2606.

[21] L. A. Zadeh, “The concept of a linguistic variable and its application to approximate reasoning—,” Information sciences, vol. 8, no. 3, pp. 199–249, 1975.

[22] S. Q. Shizhen, C. C. Chunlin, and D. D. Daoyi, “Behavior-based control of swarm robots with improved potential field,” in Proceedings of the 33rd Chinese Control Conference. IEEE, 2014, pp. 8462–8467.
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