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Fuzzy-Based Distributed Behavioral Control With Wall-Following Strategy for Swarm Navigation in Arbitrary-Shaped Environments

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ABSTRACT This paper addresses a novel fuzzy-based distributed behavioural control with the wall-following strategy for robot swarm navigation in arbitrary-shaped environments. Instead of avoiding large-sized obstacles during the swarm navigation, the proposed fully distributed control enables the robot swarm to transform from aggregation configuration to one-chain configuration and follow the obstacle boundary to overcome it. 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 behavioural 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]. Swarm robotics focuses on studying collective behaviours emerging from the interactions among robots and between robots and the environment [1]. Hence, 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 swarm navigation due to some key issues. Firstly, *local minima often occur when a robot swarm navigates through large obstacles in convex and concave shapes.* As a result, a robot could easily get trapped in a loop [3] where its control is in equilibrium, leading to motion disorientation. Secondly, *connectivity maintenance is a critical requirement for collective behaviours [4]–[6], however, it leads to the limitation of the robot mobility which is also 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. In other word, the more connectivities, the higher mobility restriction [8]. Local minimum problems of this type often appear when disturbances affect signal strength measurements and when robots move in an anti-flocking fashion. Lastly, *as swarm movement is defined as cohesive and aligned motion of individuals along a common direction, how to get an ordered motion to reach the destination is another important issue of the robot swarm navigation.* Each robot is capable of obtaining three types of information: relative distance, bearing and relative orientation of its neighbours. The relative distance and bearing are required for the cohesion control and avoid-collision control while the relative orientation is needed for the alignment control, also known as heading synchronization. Robots can easily measure the

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relative distance and bearing by using simple sensors such as infra-red, sonar [9], [10]. However, the relative orientation measurement requires a high cost of communication to constantly update the heading of neighbouring robots and elaborate sensing capabilities, e.g. digital compass, communication module, which are not always available on simple robotic platforms. Alternatively, non-alignment control can be applied to achieve the ordered motion control without estimating relative orientation, but the collective motion in this control type is achieved only if 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. 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 performs wall-following strategy inspired from Bug 2 algorithm [12] while they are in *one-chain configuration* in order to overcome large-sized obstacles. By using *one-chain configuration*, an optimal configuration without redundant connectivities, the robot swarm could stably avoid the obstacle using only the wall-following strategy without requiring complicated alignment techniques. Therefore, our approach focuses on developing a fully distributed control that possibly eliminates the local minima created by obstacles and connectivity maintenance constraints. In addition, a fuzzy-logic scheme automatically tunes control parameters and 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 consisting of large-sized obstacles.
- We proposed the *one-chain configuration* with wall-following strategy which solves all three critical issues of swarm navigation as mentioned above. Because the *one-chain configuration* is optimal in terms of connectivity links connecting robots [8], it minimizes the restriction on each robot's motion caused by connectivity maintenance leading to no 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 and 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 control 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

If the mobile robots have prior knowledge of the obstacle's shape in an environment, they can plan a path to avoid it. Otherwise, moving along the boundary of the obstacle becomes a reasonable strategy to pass the obstacle [13]. From that point of view, 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 and safe distance among robots while they move from a source to a destination. Obstacle avoidance algorithms based on potential functions are added for robot swarms to avoid small-sized obstacles [4], [11]. The ordered motion can be performed by either alignment control, which requires the neighbouring robots' relative orientation [11] or non-alignment control using the leader-followers model [4]. The alignment control facilitates motion direction synchronization, but it requires more complex sensing mechanisms to determine the neighbours' relative orientation. Non-alignment control, on the other hand, may cause heading disorientation among robots, resulting in anti-flocking situations. Furthermore, if only using the flocking algorithm, the robot swarm could face issues such as not being able to deal with large-sized obstacles, not being able to transform the swarm configuration to pass narrow passages in the environment, and 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 avoiding obstacles, robot swarms overcome the obstacle by following its boundary. Wall-following strategies mainly focused on single robot navigation, while very few are found in multi-robot systems with challenges in cooperation and interaction between robots [14]–[18]. The swarm configuration in these wall-following strategies can be categorized into three types: one-chain [16]–[18], formation [15], flexible configuration as the rolling motion in the vortex pattern [14]. In [14], as the swarm centre velocity fell, the effect of the move-to-goal action reduced and the robot swarm switched from flocking behaviour to rolling motion behaviour. The rolling motion behaviour in the vortex pattern would help the swarm follow the boundary and escape the local minimum problem caused by the u-shape obstacle. In [15], the robot swarm used communication to determine the presence of large obstacles, then activated the wall-following strategy to synchronize the

TABLE 1. Differences between the proposed approach and existing works.

	Problems addressed	Motion strategy when encountering obstacles	Swarm configuration transition	Control parameters	Maintaining connectivity	Eliminating local minima		Distributed control
						Created by Obstacles	Created by connectivity maintenance	
First category: Collective motion with obstacle avoidance strategies								
[4]	Moving from source to destination along a pre-planned path	Obstacle avoidance	NO	Pre-defined	YES	Small-sized, Convex	NO	YES
[11]	Collective motion with alignment control based on communication	Obstacle avoidance	NO	Pre-defined	NO	Small-sized, Convex	NO	NO
Second category: Collective motion with wall-following strategies								
[14]	Moving from source to destination with passing non-convex large-sized obstacles	Wall-following with pure rolling motion in vortex pattern	YES, with communication	Pre-defined	NO	Large-sized, non-convex	NO	NO
[15]	Moving from source to destination with keeping formation	Wall-following with keeping formation	NO	Pre-defined	NO	Large-sized, Convex	NO	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	Automaticaly tuned by fuzzy-logic scheme	NO	Large-sized, Convex and non-covex	NO	NO
[17]	Wall-following control	Wall-following with one-chain configuration	NO	PD controller	NO	NO	NO	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-sized, Convex and non-covex	NO	NO
Our approach	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	Automaticaly tuned by fuzzy-logic scheme	YES	Large-sized, Convex and non-covex	YES	YES

moving direction and keep the robots' formation. If more than M robots (M is predefined) in the front line of the formation detect the obstacle, the obstacle is considered as large-size obstacle. In [16], the authors developed a swarm of four robots moving in formations using communication. Robots moved sequentially in a row using the wall-following strategy when there was no space for robots to stand side-by-side. Robots also communicated to achieve consensus actions such as stop, delay, left-turn, right-turn, move-forward. In [17], the wall-following control of multi-robot systems was considered in the scenario of walls formed in polygon shapes with convex and non-convex corners. A predefined leader robot performed the wall-following strategy, and follower robots followed the leader by tracking it as a moving target. If a follower was about to collide with the obstacle, the obstacle-avoidance behaviour overrode the behaviour of leader-following. In addition, the control strategy only used local sensing information, which is the relative distance and bearing measured by infrared sensors. The developed controller was tested with two robots. In [18], the robot swarm moved from a source to destination in a formation with leader-follower flocking control. If the formation encountered obstacles that prevent the robots from maintaining their formation, it was transformed into a line formation to perform the wall-following strategy. This situation was identified in two cases: the leader suddenly received a huge repulsive force from both sides of the forward direction, or one of the robots in the boundary of the formation received a huge repulsive force from one direction. Reinforcement learning was adopted to implement the robot behavioural selection from a set of behaviours, including goal approaching, obstacle avoidance, collision avoidance, wall-following movement through predicting the robot's abilities during motion. In these few existing studies, most of them are not distributed control and require communication for configuration transition and configuration maintenance [14]–[16], [18], excepts

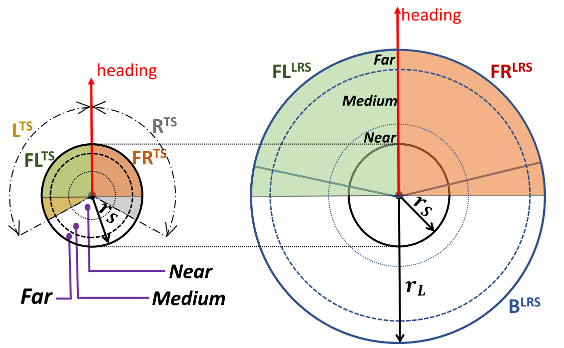

FIGURE 1. Sensing zones of tactile sensor (TS) and long-range sensor (LRS) of robot *i*. (The sensing zone of TS locates inside the sensing zone of LRS).

TABLE 2. Rule base for change of α and β (using readings of TS).

$d_{i,wp}^{TS}$ / θ_i^{TS}	FL		L		R		FR	
	α	β	α	β	α	β	α	β
Near	Z	VB	S	B	S	B	Z	VB
Medium	Z	VB	M	M	M	M	Z	VB
Far	S	B	B	S	B	S	S	B

TABLE 3. Rule base for change of γ, ν and τ (using readings of LRS).

$d_{i,j}^{LRS}$ / θ_i^{LRS}	FL			Back			FR		
	γ	ν_{ij}	τ_{ij}	γ	ν_{ij}	τ_{ij}	γ	ν_{ij}	τ_{ij}
Near	Z	Z	B	B	Z	Z	Z	Z	B
Medium	Z	M	M	B	Z	Z	Z	M	M
Far	S	B	Z	B	Z	Z	S	B	Z

for [17] that only considers the wall-following control without configuration transition.

Table 1 summarizes the differences between our proposed approach and the existing works on robotic swarms using the wall-following strategy. 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 communication. The proposed control ensures the connectivity maintenance of the robot swarm and solves local minimum problems derived from both the large-sized 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 MODELING

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 close-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 neighbour robots of robot i. N_i denotes a set of neighbours 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 behaviours (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 $d_{i,wp}^{TS}$ and bearing θ_i^{TS} readings of TS are mapped into corresponding sensor partitions using input MFs in Fig. 2(a)&(b). Similarly, $d_{i,j}^{LRS}$ and θ_i^{LRS} of LRS are mapped using input MFs in Fig. 2(c) and (d). Fuzzy antecedent variable of $d_{i,wp}^{TS}$ and $d_{i,j}^{LRS}$ are evaluated with the fuzzy sub-sets of *Near, Med (Medium), Far*, whereas θ_i^{TS} and θ_i^{LRS} 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.
- Then, a set of if-then rules are 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 *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 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 that guarantees the integrity preservation of the robot swarm without

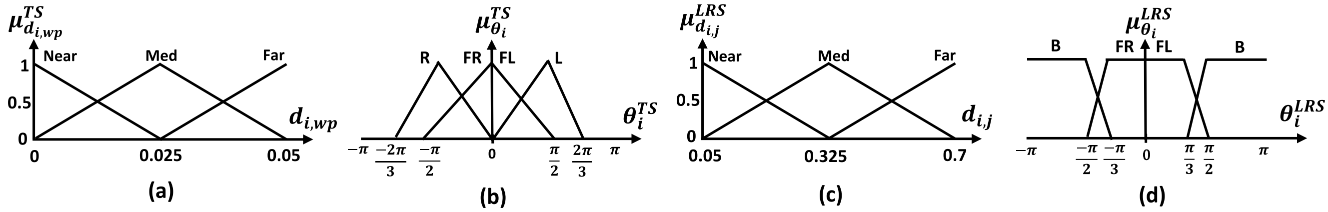

FIGURE 2. Input membership function plots: (a) For distance deviation of TS. (b) For angular deviation of TS. (c) For distance deviation of LRS. (d) For angular deviation of LRS.

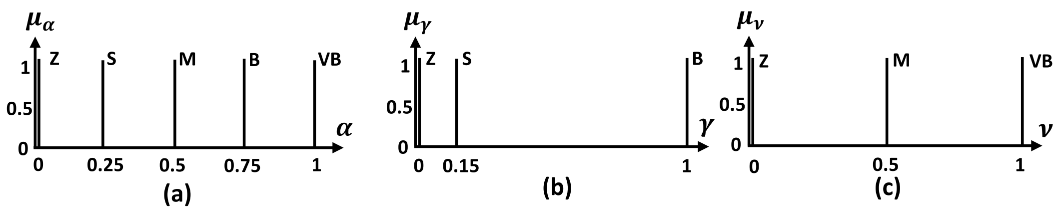

FIGURE 3. Output membership function plots: (a) For control parameters α and β. (b) For control parameter γ. (c) For control parameters ν and τ.

loss of members and the information exchange among neighbour robots. The information exchanged is not used as the input for our proposed controller; instead, it will be used to establish an intelligent sensor network in our future publication. When robot i tends to lose connectivity with its critical neighbours N_i^c, its mobility constraint is activated to adjust its maximum velocity ($V_{i_{max}} = \Delta_i/T_C$) through the normalization of its run-step Δ_i ($\Delta_i \leq \varepsilon_i/2$), where T_C is the control period and $\varepsilon_i = \min\limits_{j \in N_i^c}(r_L - r_{ij}) \leq \varepsilon$. ε and ε_i are critical tolerance and minimum tolerance of robot i, respectively. As a result, connectivities are always maintained.

D. SWARM CONFIGURATIONS

Swarm configurations are emerging while robots are cooperating and interacting with the environment. We categorize swarm configurations into two primary morphologies:

- *One-chain configuration*: the swarm configuration is considered one-chain if no robot has more than two nearest neighbours. That is, a robot i has only one or two direct connectivities with its neighbours (similar to Definition 5 in [8]). One-chain configuration results from the minimization process of redundant connectivities, turning complex connectivity topologies into the minimal form and removing local minima caused by connectivity maintenance constraints.
- *Aggregation configuration*: the swarm configuration is considered as aggregation if any robot in the swarm has more than two nearest neighbours; that is, a robot i has more than two direct connectivities with its neighbours.

IV. FUZZY-BASED DISTRIBUTED BEHAVIOURAL CONTROL

The core concept of our paper is to design a control for a robot swarm 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 section III-B) and synthesized controllers as in Fig. 4.

We used different synthesized controllers to generate different desired swarm behaviours: 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 behaviours: 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.

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 $\overrightarrow{v}_i^{wps}$, wall-pulling $\overrightarrow{v}_i^{wpl}$ and move-along-the-wall $\overrightarrow{v}_i^{matw}$ behaviours. This strategy is activated when the distance between robot i and boundary of an 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.

$$\overrightarrow{V_{WF}} = \overrightarrow{v}_i^{matw} + \overrightarrow{v}_i^{wps} + \overrightarrow{v}_i^{wpl} \tag{1}$$

1) MOVE-ALONG-THE-WALL BEHAVIOUR

This behaviour 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

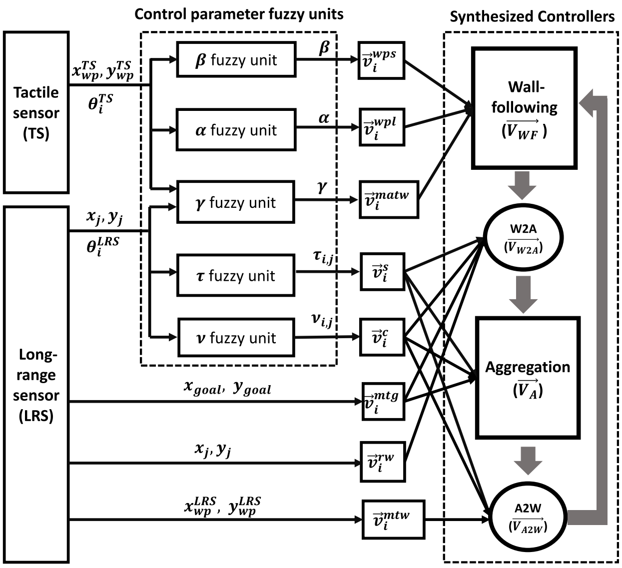

FIGURE 4. Fuzzy-based distributed behavioural control diagram.

Algorithm 1: The Switching Algorithm

Input: wp_{TS}, wp_{LRS}

Output: $\overrightarrow{V_i}$

if $\exists wp_{TS}$ **then**

  $\overrightarrow{V_i} = \overrightarrow{V_{WF}} = \overrightarrow{v}_i^{matw} + \overrightarrow{v}_i^{wps} + \overrightarrow{v}_i^{wpl}$;

else if $\nexists wp_{LRS}$ **then**

  $\overrightarrow{V_i} = \overrightarrow{V}_A = \overrightarrow{v}_i^{c} + \overrightarrow{v}_i^{s} + \overrightarrow{v}_i^{mtg}$;

else if $\exists wp_{LRS}$ **then**

  if *Robot i does not have LoS with the given target point* **then**

    $\overrightarrow{V_i} = \overrightarrow{V}_{A2W} = \overrightarrow{v}_i^{mtw} + \overrightarrow{v}_i^{c} + \overrightarrow{v}_i^{s}$;

  else

    $\overrightarrow{V_i} = \overrightarrow{V}_{W2A} = \overrightarrow{v}_i^{rw} + \overrightarrow{v}_i^{c} + \overrightarrow{v}_i^{s} + \overrightarrow{v}_i^{mtg}$;

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detected by the tactile sensor of robot i is wp_{TS} $(x_{wp}^{TS}, y_{wp}^{TS})$ $(wp_{TS} \in W)$, we have:

$$\overrightarrow{v}_i^{matw} = \gamma \begin{bmatrix} -(y_{wp}^{TS} - y_i) \\ (x_{wp}^{TS} - x_i) \end{bmatrix} \tag{2}$$

γ fuzzy unit is used to calculate the control parameter γ for this behaviour. γ is determined for the input antecedent variables $d_{i,j}^{LRS}$ and θ_i^{LRS} using rules in Table 3, and subjects to ouput MFs in Fig. 3 (b). $d_{i,j}^{LRS}$ and θ_i^{LRS} are the relative distance and angle towards the closest neighbouring robot j in the front, respectively.

2) WALL-PUSHING BEHAVIOUR

This behaviour makes robot i not to collide with the wall while performing wall-following strategy.

$$\overrightarrow{v}_i^{wps} = \beta \begin{bmatrix} (x_i - x_{wp}^{TS}) \\ (y_i - y_{wp}^{TS}) \end{bmatrix} \tag{3}$$

The control parameter β of this behaviour is computed by β fuzzy unit. β is determined for the input antecedent variables $d_{i,wp}^{TS}$ and θ_i^{TS} using rules in Table 2, and subjects to ouput MFs in Fig. 3 (a). $d_{i,wp}^{TS}$ and θ_i^{TS} are the relative distance and angle towards the closest point on the boundary of the obstacle wp_{TS}, respectively.

3) WALL-PULLING BEHAVIOUR

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

$$\overrightarrow{v}_i^{wpl} = \alpha \begin{bmatrix} (x_{wp}^{TS} - x_i) \\ (y_{wp}^{TS} - y_i) \end{bmatrix} \tag{4}$$

The control parameter α is calculated by α fuzzy unit. α is determined for the input antecedent variables $d_{i,wp}^{TS}$ and θ_i^{TS} using rules in Table 2, and subjects to ouput 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 $\overrightarrow{v}_i^{c}$, separation $\overrightarrow{v}_i^{s}$ and move-to-goal $\overrightarrow{v}_i^{mtg}$ 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:

$$\overrightarrow{V}_A = \overrightarrow{v}_i^{c} + \overrightarrow{v}_i^{s} + \overrightarrow{v}_i^{mtg} \tag{5}$$

1) COHESION BEHAVIOUR

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.

$$\overrightarrow{v}_i^{c} = \sum_{j \epsilon N_i \setminus N_i^{near}} \nu_{ij} \begin{bmatrix} (x_j - x_i) \\ (y_j - y_i) \end{bmatrix} \tag{6}$$

where ν_{ij} is the control parameter corresponding to robot i and its neighbouring robot $j \in N_i \setminus N_i^{near}$.

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

2) SEPARATION BEHAVIOUR

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

$$\overrightarrow{v}_i^{s} = \sum_{j \epsilon N_i \setminus N_i^{far}} \tau_{ij} \begin{bmatrix} (x_i - x_j) \\ (y_i - y_j) \end{bmatrix} \tag{7}$$

where τ_{ij} is the control parameter corresponding to robot i and its neighbouring robot $j \in N_i \setminus N_i^{far}$.

τ fuzzy unit is used to calculate the control parameter τ_{ij} for this behaviour. τ_{ij} is determined for the input antecedent variables $d_{i,j}^{LRS}$ and θ_i^{LRS} using rules in Table 3, and subjects to ouput MFs in Fig. 3 (c).

3) MOVE-TO-GOAL BEHAVIOUR

This behaviour is the driven factor making robot i achieve its target by pushing it toward the *goal* position $g(x_g, y_g)$.

$$\overrightarrow{v}_i^{mtg} = \begin{bmatrix} (x_g - x_i) \\ (y_g - y_i) \end{bmatrix} \tag{8}$$

C. TRANSITION MODES

The wall-following and aggregation strategies are synthesized controllers which enable swarm navigation in 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 are 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 behaviour* ($\overrightarrow{v}_i^{mtw}$) is created to drive robot i closer to boundary of obstacles until the wall-following strategy is activated.

$$\overrightarrow{v}_i^{mtw} = \begin{bmatrix} (x_{wp}^{LRS} - x_i) \\ (y_{wp}^{LRS} - y_i) \end{bmatrix} \tag{9}$$

where the coordinate of the closest point on the obstacle's boundary detected by the LRS of robot i is $wp_{LRS}\,(x_{wp}^{LRS}, y_{wp}^{LRS})$, where $wp_{LRS} \in W$ and $r_S < \|wp_{LRS} - i\| \leq r_L$.

This transition mode consists of three individual behaviours: cohesion $\overrightarrow{v}_i^{c}$, separation $\overrightarrow{v}_i^{s}$ and move-to-wall $\overrightarrow{v}_i^{mtw}$. 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:

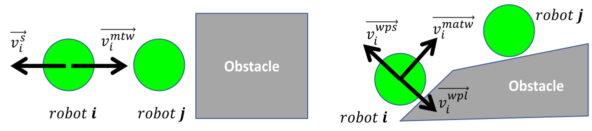
$$\overrightarrow{V}_{A2W} = \overrightarrow{v}_i^{mtw} + \overrightarrow{v}_i^{c} + \overrightarrow{v}_i^{s} \tag{10}$$

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. *Random-walk behaviour* $\overrightarrow{v}_i^{rw}$ is activated when robots exit the obstacle's boundary. This behaviour creates chaos for aggregation configuration to form and is defined as a perpendicular vector connecting two neighbour robots ($j, k \in N_i$).

$$\overrightarrow{v}_i^{rw} = \begin{bmatrix} \pm(y_k - y_j) \\ \mp(x_k - x_j) \end{bmatrix} \tag{11}$$

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



(a) aggregation-to-wall-following mode (b) wall-following strategy

FIGURE 5. Two synthesized controllers are used to overcome local minima.

The W2A mode is activated when the robot i's LRS 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:

$$\overrightarrow{V}_{W2A} = \overrightarrow{v}_i^{rw} + \overrightarrow{v}_i^{c} + \overrightarrow{v}_i^{s} + \overrightarrow{v}_i^{mtg} \tag{12}$$

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 minimum problems appear in environments with large and concave obstacles, and narrow channels. Moreover, in robot swarm navigation, we must add the collision avoidance among robots, thus the system is more prone to local minima.

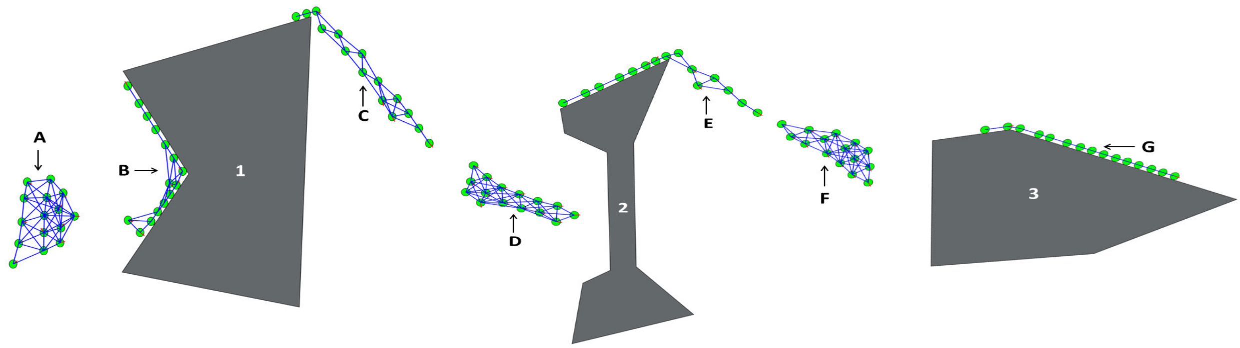
In our proposed method, there are two states that the robots could fall into local minima caused by competing forces: 1) when the robots approach the obstacle, and 2) when the robots contour the obstacle's boundary. Local minima in these two states could be avoided by using two proposed synthesized controllers: aggregation-to-wall-following mode and wall-following strategy.

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

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. For example, when robot i gets too close to robot j as in Fig. 5, 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. Robot j will keep moving closer to the obstacle or along the wall, making room for robot i to approach the wall because the frontal robot j is either in A2W mode or WF strategy.

V. EXPERIMENT RESULTS AND DISCUSSION

In this section, we present the results of a simulation and a real experiment in an environment consisting of both convex



(a) Obstacle 1: concave (b) Obstacle 2: concave (c) Obstacle 3: convex

FIGURE 6. A simulation of the swarm of 15 robots passing three large obstacles.

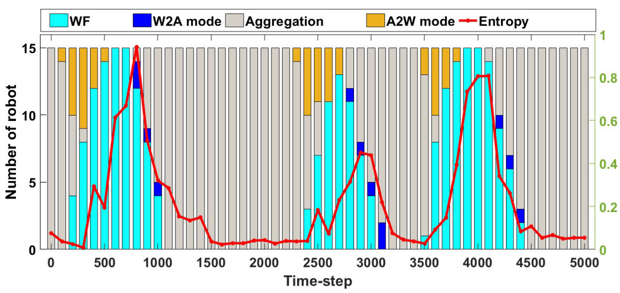


FIGURE 7. Correlation of number of robots and entropy metric in simulation.

and non-convex obstacles and evaluate the performance of the proposed control system.

A. EXPERIMENT SETUP

In the simulation and real experiment, we used differential-drive mobile robots which are identical and in round shapes with a diameter of 10 cm. The TS range was set at 5cm and the LRS range was set at 70 cm. The critical tolerance ε and the control period T_C are set at 0.06 m and 0.1 s respectively; thus, the maximum speed V_{max} of each robot is 0.3 m/s calculated using the equation in section III-C. 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 $m \times 9$ m containing one large convex obstacle and two large concave obstacles arranged randomly in order to prevent the swarm from reaching its destination Fig. 6. The real experiment was carried out with six robots in the arena of 4m $\times$ 3m with one concave large obstacle as illustrated in Fig. 8. A motion-tracking system was used to reduce the difficulties of representing sensors 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 *entropy*. A drop in entropy value indicates an aggregation, 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:

$$H(h) = \sum_{z=1}^{M} p_z \log_2 p_z \tag{13}$$

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 ∞ of h to find the total entropy S:

$$S = \int_0^\infty H(h)dh \tag{14}$$

C. RESULTS AND DISCUSSION

In the simulation,[1] we examined how the distributed control guided a robot swarm to navigate through convex and concave obstacles. Initially, all the robots were in the aggregation configuration as in Fig. 6(A). They did not observe any obstacle and 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 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

[1]Simulation: `https://youtu.be/L75EBAfDrVM`

obstacles 2 and 3, an appropriate synthesized controller was selected by each robot using algorithm 1; 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 described in section III-B.

To evaluate the effectiveness of synthesized controllers in swarm configuration transformation, we analyzed the correlation of the number of robots 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 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(*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 leaving the obstacle, the majority gradually switched to W2A mode and then aggregation strategy as depicted in Fig.6(*C*). As a result, the entropy decreased from 1 back to 0.05; which indicates the 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 robots to communicate for controller synchronization or behaviour 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 dealing with local minima caused by obstacles and connectivity maintenance thanks to the distributed control shown in Fig. 4. Because each robot followed the boundary of obstacles in WF strategy and eventually formed a one-chain configuration, the robot swarm could overcome any local minima caused by obstacle of any shapes. Moreover, 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 a real experiment[2] with a swarm of six mobile robots passing a concave obstacle as shown in Fig. 8.

[2]Real experiment: `https://youtu.be/NLSUcJrdHdk`

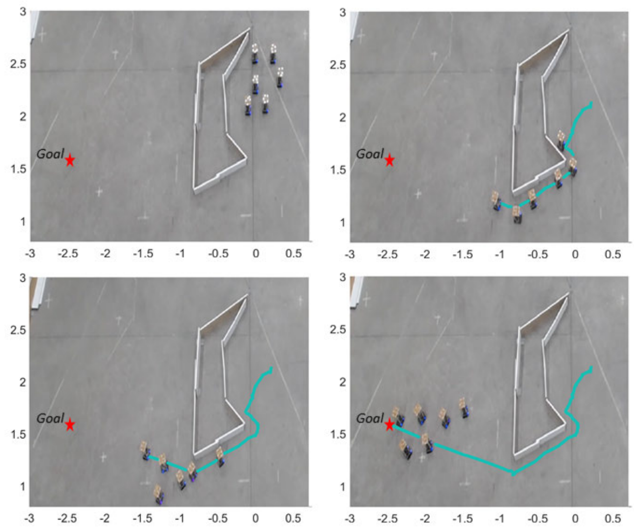


FIGURE 8. Snapshots of the swarm of six real robots passing a concave obstacle.

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. In contrast, when we applied a simple flocking algorithm which only has three basic behaviour: 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 and 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 experiment. Moreover, each synthesized controller's control parameters are automatically tuned by using our control parameter fuzzy units. In the future, we aim to examine aspects of layered wall-following strategy and active tactile-based swarming behaviours.

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