Fuzzy Manual Control of Multi-Robot System with Built-In Swarm Behavior

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***Abstract* — Swarm robotics is a decentralized control architecture, where global behavior emerges as a result of local interactions between neighboring robots. The deficiency of the swarm behavior model is the stochastic nature of movement patterns, which reduces its applicability, when precise maneuvering is needed. This paper alleviates this problem by introducing fuzzy manual control of a multi-robot system utilizing the swarm behavior model. The built-in swarm behavior controls low level tasks such as formation keeping and obstacle avoidance. A fuzzy controller works as an intelligent mechanism for tuning the manual control signal received by the robots. The main advantages of the presented algorithm are: 1) deliberating the operator from low level maneuvering tasks; 2) single operator control of multi-robot group; 3) robustness, flexibility and scalability. The presented architecture was implemented and tested in a simulation environment. The introduced system can significantly improve the performance of search and rescue operations as well as exploration of dangerous environments.**

***Keywords* — Exploration, Fuzzy Control, Multi-Robot System, Search and Rescue, Swarm Robotics.**

I. Introduction

SWARM robotic, first introduced in [1], is an attractive and relatively new area of research. It specializes at mimicking the behavior patterns observed in social insects [2]-[4]. This parallel is used in the field of collective robotics [5], [6]. As opposed to the centralized control of larger robotic groups, swarm behavior model is based on the concept of sensing only local neighborhood and acting accordingly [7]. It was shown that collective behavior emerges in the system even if no group leadership, hierarchical control and global information are present [8]-[10].

Intelligent and expensive autonomous mobile robots are commonly used either for solo operations or working in small groups [11]. On the other hand, robotic swarm consists of a large number of homogenous autonomous relatively incapable or inefficient robots with only local sensing and communication capabilities [12]. The main advantages of swarm robotics are robustness, flexibility and scalability of the system.

The deficiency of the purely decentralized control mechanism is the stochastic nature of the movement patterns of the robotic swarm [13], [14]. This randomness of the emergent global behavior decreases the applicability of the robotic swarm in applications, where precise manual control is needed. Considerable research has been done in combining the behavior based control with classical navigation using predefined path or a set of checkpoints [15]-[17]. But to the best of our knowledge, an approach for combining the swarm behavior with manual control is missing.

This paper presents an algorithm for a fuzzy manual control of multi-robot system with a built-in swarm behavior. The behavior model is responsible for low-level navigation tasks such as formation keeping and obstacle avoidance. The received manual control signal is tuned by a fuzzy controller. The controller works as an adaptive intelligent mechanism and improves the maneuvering performance of the robotic group. The implemented system combines the robustness, flexibility and scalability of swarm robotics with full control and precise maneuvering of classical manual control.

The proposed system can be applied in areas, where the use of a single robot is insufficient. The specific applications can be search and rescue operations, dangerous environment exploration or surveillance. For instance, during a search and rescue operation the robotic swarm is deployed in the target environment. The operator can navigate the group precisely towards the area of interest. The proposed algorithm deliberates the operator from low-level navigation tasks such as formation keeping and obstacle avoidance. At the same time the swarm is covering a large area of the searched environment, thus leading to a faster localization of possible victims.

The rest of the paper is organized as follows. Section 2 describes the implemented model of swarm behavior. Section 3 introduces the fuzzy manual control algorithm. Section 4 presents the experimental results achieved during the simulation of the proposed architecture. Final conclusions and proposals for further work are given in section 5.

II. Swarm Behavior Model

The swarm behavior model, implemented in each robot, follows the original concept proposed by Reynolds [18]. Each robot is capable of local perception of other robots and obstacles in its local environment. The behavior of

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individuals is guided by local repulsion, alignment and attraction. Each robot maintains a minimum distance to others at all times – the repulsion behavior. If not performing repulsion maneuver, robots are attracted by others and tend to align with their neighbors – the orientation and attraction behavior.

Circular local sensing zones around each robot were adopted from [19]. Zone of repulsion (*ZOR*) being the closest to the robot followed by the zone of orientation (*ZOO*) and the zone of attraction (*ZOA*). Fig. 1 illustrates the local sensing zones. The robot is located in the middle of the zones (black dot). The radius of particular local sensing zone is denoted by r^{ZOR}, r^{ZOO} and r^{ZOA} respectively. First the directional vectors of particular behaviors are calculated. Then the behaviors are combined into a final vector and the steering angle for modifying the directional vector of robot's movement is computed.

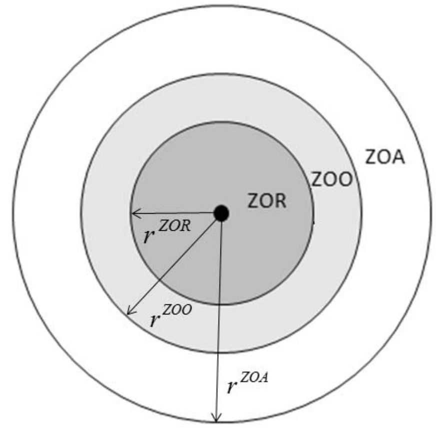


Fig. 1. Local sensing zones maintained by each robot.

A. Computation of Directional Vectors

As described in [19], each robot tries to avoid the presence of any other robots in its *ZOR* by steering away. Similarly each robot is attracted by its neighbors in the *ZOA* and attempts to steer towards them. Finally each robot tends to align its direction with the average direction of its neighbors in its *ZOO*. Additionally, in order to prevent a collision, each robot tries to steer away from the nearest obstacle in its *ZOR*.

Following the description in [19], if there are N_{ZOR} robots located in the *ZOR* of robot *i*, then the directional vector of the repulsion behavior is computed as:

$$\vec{v}_R = \begin{cases} \vec{v}_{Dir} & , N_{ZOR} = 0 \\ -\dfrac{1}{N_{ZOR}} \displaystyle\sum_{j=1}^{N_{ZOR}} \dfrac{(\vec{p}_j - \vec{p}_i)}{|\vec{p}_j - \vec{p}_i|} & , N_{ZOR} > 0 \end{cases} \quad (1)$$

Here $\vec{p}_i$ and $\vec{p}_j$ denote the position of robot *i* and its neighbors respectively and $\vec{v}_{Dir}$ stands for the direction of movement of robot *i*.

If there are N_{ZOA} robots in the *ZOA* and N_{ZOO} robots in the *ZOO* of robot *i*, then the directional vectors of the attraction and orientation behavior are given as:

$$\vec{v}_A = \begin{cases} \vec{v}_{Dir} & , N_{ZOA} = 0 \\ \dfrac{1}{N_{ZOA}} \displaystyle\sum_{j=1}^{N_{ZOA}} \dfrac{(\vec{p}_j - \vec{p}_i)}{|\vec{p}_j - \vec{p}_i|} & , N_{ZOA} > 0 \end{cases} \quad (2)$$

$$\vec{v}_O = \begin{cases} \vec{v}_{Dir} & , N_{ZOO} = 0 \\ \dfrac{1}{N_{ZOO}} \displaystyle\sum_{j=1}^{N_{ZOO}} \dfrac{\vec{v}_j}{|\vec{v}_j|} & , N_{ZOO} > 0 \end{cases} \quad (3)$$

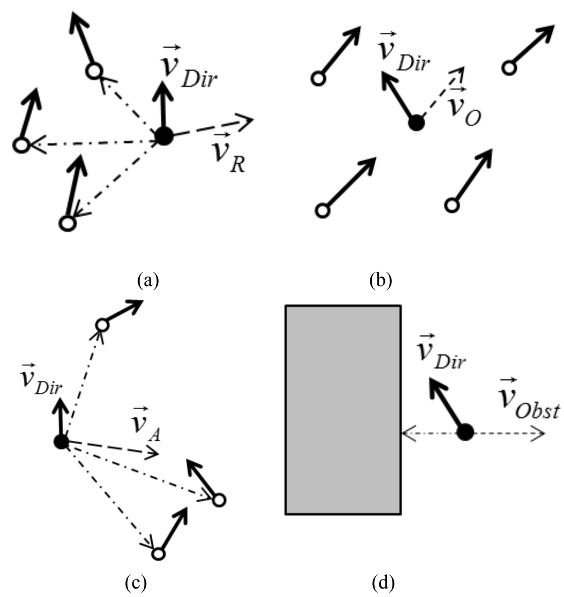


Fig. 2. Computation of the repulsion (a), orientation (b), attraction (c) and obstacle avoidance (d) behaviors.

Here $\vec{v}_j$ denotes the direction of movement of robot *j*.

In addition, vector $\vec{v}_{Obst}$ is computed as the vector pointing away from the nearest obstacle located in the *ZOR* of robot *i*.

Fig. 2 describes the computation of the directional vectors for particular behaviors.

B. Combining Directional Vectors

To determine the combined directional vector $\vec{v}_C$, the priority of particular behaviors has to be considered. In the presented algorithm the obstacle avoidance is assigned the highest priority. Further, as defined in [19], if there are robots in the *ZOR* of particular robot, the repulsion behavior inhibits the other behaviors. If there are only robots presented in the *ZOA* and *ZOO* of the given robot, then the final directional vector is obtained as an average of the attraction and orientation directional vectors.

The rules are summarized in the following equation:

$$\vec{v}_C = \begin{cases} \vec{v}_{Obst}, & \text{if } N_{Obst} > 0 \\ \vec{v}_R, & \text{if } N_{Obst} = 0 \wedge N_R > 0 \\ \vec{v}_O, & \text{if } N_{Obst}, N_R, N_A = 0 \wedge N_O > 0 \\ \vec{v}_A, & \text{if } N_{Obst}, N_R, N_O = 0 \wedge N_A > 0 \\ \frac{1}{2}(\vec{v}_O + \vec{v}_A), & \text{if } N_{Obst}, N_R = 0 \wedge N_O, N_A > 0 \end{cases} \quad (4)$$

C. The Steering Angle

The computed combined directional vector $\vec{v}_C$ for robot i is transformed into a steering angle α_S. Steering angle determines the relative change to the vector of movement $\vec{v}_{Dir}$ of robot *i*. It is computed based on the angular difference between vectors $\vec{v}_{Dir}$ and $\vec{v}_C$. The sign of the steering angle α_S determines the direction of the update.

An upper bound on the amplitude of the steering angle is determined by the maximum turning rate θ. If the amplitude of the computed steering angle α_S exceeds the parameter θ, it is decreased to the value of θ:

$$\alpha_S = \begin{cases} \alpha_S, & \text{if } |\alpha_S| \le \theta \\ \theta, & \text{if } \alpha_S > 0 \wedge |\alpha_S| > \theta \\ -\theta, & \text{if } \alpha_S < 0 \wedge |\alpha_S| > \theta \end{cases} \quad (5)$$

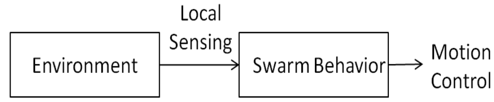
III. Fuzzy Manual Control of Robotic Swarm

In parallel with computing the swarm behavior model, every robot receives a manual control signal. The signal is tuned by a fuzzy controller and combined with the output of the swarm behavior model. The combined result is applied to the robot.

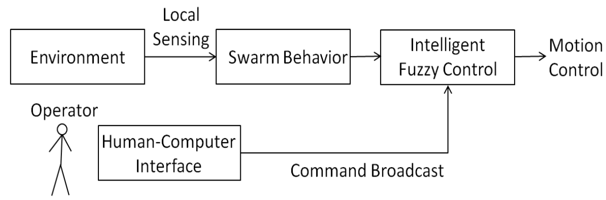
The motion control using only the swarm behavior model is depicted in Fig. 3a. The robot senses its local environment, evaluates the swarm behavior model and applies the computed result to the motion control. Fig. 3b shows the presented fuzzy manual control architecture. The intelligent fuzzy control block was added into the system. This block first receives the manual control signal from a human-computer interface station. The control signal is adjusted by the intelligent fuzzy controller based on the evaluation of the local environment. The modified signal is combined with the output of the swarm behavior model and finally applied to the motion control of the robot.

A. Manual Control Signal

In the presented algorithm, three degrees of freedom of the swarm movement were identified. In particular, the operator can control the speed, the direction of movement and the radius of the local sensing zones of the robotic swarm. The control signal is broadcasted from the operator's interface to all robots. The individual robots do not send any information about their position or direction



(a)



(b)

Fig. 3. Diagram a motion control mechanism using only the swarm behavior model (a) and the fuzzy manual control with built-in swarm behavior (b).

back to the operator.

The control signal contains three commands. Command Δ_{Speed} is used to update the speed of the robots. Command Δ_{Zones} modifies the radius of the local sensing zones. And command Δ_{Angle} contains the relative angular update of the current directional vector of the robot. Both Δ_{Speed} and Δ_{Zones} are expressed as percentage difference between the actual and the desired value. For instance, after receiving the control signal $\{\Delta_{Speed} = 0.02, \Delta_{Zones} = -0.05, \Delta_{Angle} = -3\}$, the robots should speed up by 2%, decrease the radius of their local sensing by 5% and steer to the right by 3 degrees.

The intelligent controller applies the received control commands Δ_{Speed} and Δ_{Zones} directly to the robot. Speed s_i of robot i is updated as:

$$s_{i,t+1} = s_{i,t}\left(1 + \Delta_{Speed}\right) \quad (6)$$

Similarly, the new radii of the local sensing zones r_i^{ZOR}, r_i^{ZOO} and r_i^{ZOA}, which are depicted in Fig. 1, are computed as:

$$r_{i,t+1}^{ZOR} = r_{i,t}^{ZOR}\left(1 + \Delta_{Zones}\right) \quad (7)$$

$$r_{i,t+1}^{ZOO} = r_{i,t}^{ZOO}\left(1 + \Delta_{Zones}\right) \quad (8)$$

$$r_{i,t+1}^{ZOA} = r_{i,t}^{ZOA}\left(1 + \Delta_{Zones}\right) \quad (9)$$

The control command Δ_{Angle} is first adjusted by the fuzzy controller, before the robot's directional vector $\vec{v}_{Dir}$ is updated. The fuzzy controller is described in the following section.

B. The Intelligent Fuzzy Control

The decentralized swarm behavior model is responsible for a global coherent flocking motion of the robotic group. When maneuvering through an environment, individual robots might temporarily become incoherent with the

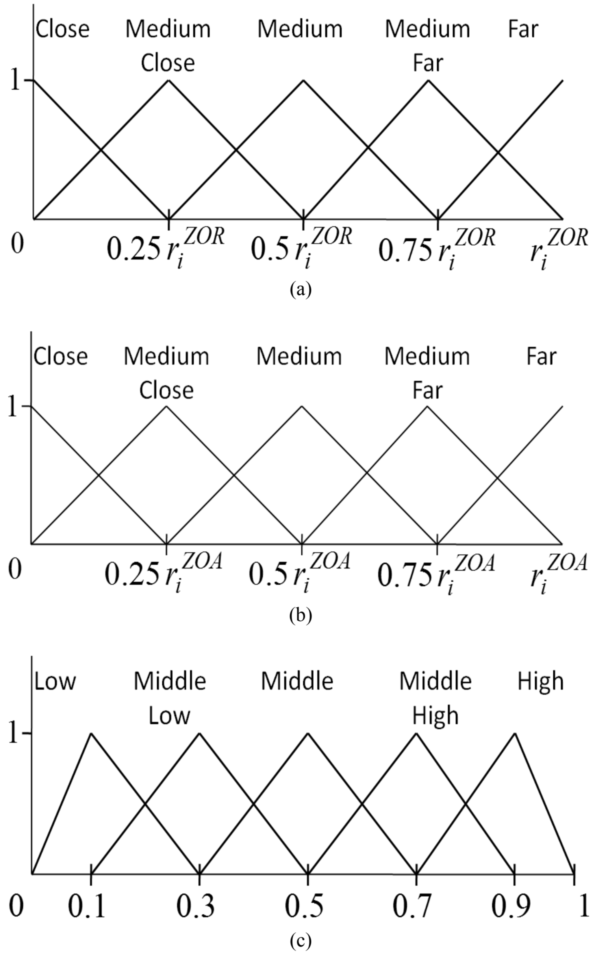


Fig. 4 Fuzzy representation of concepts distance from an obstacle (a), separation from the swarm (b) and the integrity of the swarm (c).

swarm movement. For instance, this can happen when robots try to avoid a collision with an obstacle.

Applying manual control command Δ_{Angle} to robots, which are temporarily misaligned with the rest of the swarm, might result in further compromising the integrity of the group. Consequently the performance of the manual control would be significantly reduced. The fuzzy controller tunes the manual control command Δ_{Angle} in order to prevent such a scenario.

Two main situations posing the most danger on the compactness of the swarm were identified as:

1) Obstacle avoidance

2) Separation from the swarm

In the first case, the manual control signal should be suppressed so that the robot can successfully avoid the collision with the obstacle. Similarly in the second case, the manual control signal should be suppressed as well. In this way the swarm behavior is emphasized and the robot aligns back with the swarm.

Using the previously computed value of α_S (5) and the received manual command Δ_{Angle}, the final steering angle α_i for robot i is computed as follows:

$$\alpha_i = \frac{\alpha_S + \mu \Delta_{Angle}}{1+\mu} \tag{10}$$

Here μ is used to suppress the manual control command. The value of μ is computed using a fuzzy controller [20], [21]. Fuzzy representation of the concept distance from an obstacle is shown in Fig. 4a. Fuzzy representation for the concept separation from the swarm, shown in Fig. 4b, is computed based on the mean distance from the 4 nearest neighbors of robot *i*. If some of the nearest neighbors are located outside of the *ZOA* of robot *i*, then they are assigned the distance r_i^{ZOA}. The value of the output fuzzy concept integrity of the swarm is modeled as shown in Fig. 4c.

The output of the fuzzy controller is calculated using the triangular membership functions and Zadeh's max-min composition [22].

The final steering angle α_i is used to modify the robot's directional vector $\vec{v}_{Dir}$.

IV. Experimental Results

To demonstrate the performance of the presented algorithm, a virtual simulation environment was written in C++ programming language. Three experiments were designed to test different parts of the system. First the operator's ability to maneuver the multi-robot group was demonstrated. Then the robustness of the system was shown by simulating communication failures between the operator and the robots. In the last experiment, the performance of the fuzzy controller was evaluated.

A. Maneuvering the Swarm

During this test, a group of robots performs an exploration task, simulating a search and rescue operation. The robots are deployed in an indoor environment consisting of open rooms connected by narrow corridors. The swarm has to spread out in order to cover as much area of the open rooms as possible. However, the group has to maintain a tight formation when passing to another room through the narrow corridors (possibly pipeline or tunnels).

Fig. 5 shows the recorded trajectories of a multi-robot group consisting of 10 robots. The operator maneuvers the swarm from the bottom of the environment through the narrow zigzag corridor to the upper room. It is demonstrated that the operator can control the formation and the direction of movement of the group as desired. By increasing the radii r^{ZOR}, r^{ZOO} and r^{ZOA}, the robots spread out to cover larger areas. By decreasing the radii, the robots are forced to come together to negotiate narrow passages. This mechanism results in an efficient maneuvering, enabling the operator to control the movement of the swarm without major collisions with obstacles.

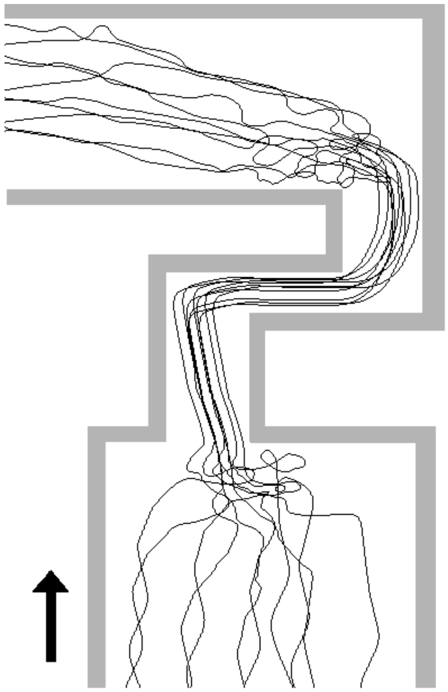


Fig. 5. Trajectories of the multi-robot group as it maneuvers through a narrow corridor between two rooms. The arrow shows the direction of movement.

B. Robustness of the System

Robust communication is one of the biggest issues of remote robot control in real world. Loss of communication usually leads to losing the control over the robot.

This experiment was designed to test the robustness of the algorithm by simulating coommunication failures between the operator and a certain number of robots. Robot, which was having a communication failure, was receiving no manual control commnad Δ_{Angle} for update of its directional vector. The operator had to perform a simple maneuver consisting of navigating a group of 10 robots between two square-shaped obstacles. In consecutive runs, the number of robots having a communication failure was increased. Fig. 6 shows the recorded trajectories of the robotic swarm. The top picture illustrates the desired maneuver. Underneath, from the top to the bottom, the number of robots having a communication failure was increased from 0, to 5, 8 and 9.

From Fig. 6 it can be observed that as the number of robots having a communication failure is increasing, the trajectories are drifting away from the optimal path. However, even with 9 out of 10 robots from the whole group having a communication failure, the operator still has enough control to complete the desired maneuver. This is a result of the swarm behavior model that forces the robots to align with their neighbors.

C. Fuzzy Controller Evaluation

In this experiment, the performance of the fuzzy controller was evaluated. Its output was recorded during the two hazardous scenarios identified in section III B (obstacle avoidance and swarm separation). In the first case the robot was purposely separated from the rest of swarm. The recorded response of the fuzzy controller is plotted in Fig. 7a, along with the mean distance to its 4 nearest neighbors d_N. In the second case the robot was intentionally navigated towards an obstacle. The plot of the response is shown in Fig. 7b, along with the distance to the obstacle d_O.

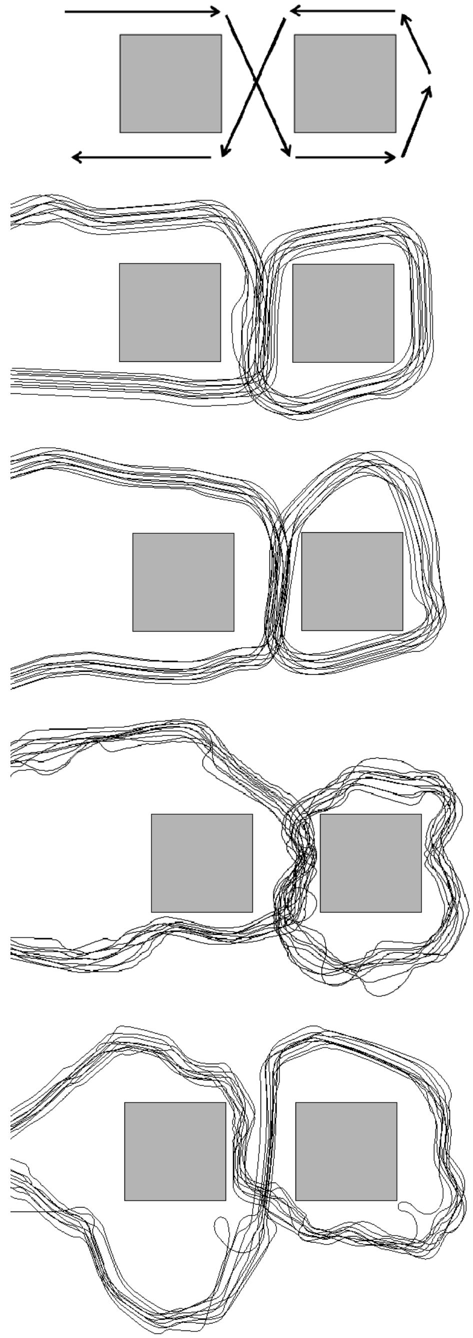


Fig. 6. Trajectories of the swarm performing a simple maneuver. The top diagram shows the desired maneuver. Bellow, the communication failure is simulated.

The first case, as the robot is separated from the rest of the swarm (around time 75 and 280), the fuzzy controller detects the hazardous situation and temporarily suppresses the manual control signal. As the robot returns to the swarm (around time 110 and 400), the control is handed back to the operator.

In the second case, it can be observed that as the robot is approaching closer to an obstacle (around time 35), the manual control signal is again suppressed by the output of

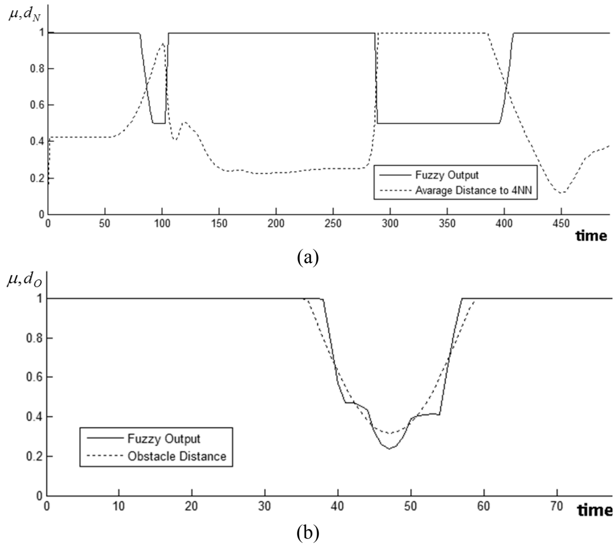


Fig. 7. The output of the fuzzy controller for a robot getting separated from the swarm (a) and approaching an obstacle (b).

the fuzzy controller. When the robot avoids the obstacle and maneuvers further away (around time 55), the control is again handed back to the operator. This prevents the operator from endangering the robot as well as posing risk to the environment.

V. Conclusion and Further Work

An algorithm for fuzzy manual control of multi-robot system with built-in swarm behavior was presented in this paper. The swarm behavior model controls the low-level navigation tasks such as maintaining formation and obstacle avoidance. The fuzzy controller, implemented on the top of the existing swarm behavior, adjusts the manual control signal to improve the performance of the system.

Experimental testing demonstrated that the operator maintains efficient control for correct maneuvering of the swarm. Furthermore, the robustness of the system was demonstrated by simulating communication failures for individual robots. The operator was able to perform the desired maneuver even when 9 out of 10 robots stopped receiving the manual control signal. The performance of the fuzzy control was shown to correctly recognize hazardous situations and adjust the manual control signal appropriately.

Suitable force-feedback haptic devices are currently considered for a use with the presented algorithm. Adding a tactile augmentation would create a complete system for a precise manual navigation of multi-robot group.

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