A Dynamic Leader-Follower Strategy for Multi-robot Systems

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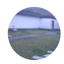

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A Dynamic Leader-Follower Strategy for Multi-Robot Systems

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***Abstract*—Since there is not a very suitable dynamical leader selection model for formations control of the multi-robot system, we propose an affection-based dynamic leader selection strategy. A leader selection modular is used to switch the leader autonomously according to the cognized environmental statement based on two virtual affections, disappointment and abashment. The disappointment of followers will increase with the time spending in the awful scenario. When it exceeds a certain threshold, the followers will broadcast an unsatisfied signal. The abashment value of leader changes with the unsatisfied signals received from the followers and flutters with its own status at the same time. When the abashment value goes beyond the threshold, the leader re-selection process will be triggered. The abashment threshold is determined by the theoretic calculation. Plenty of simulation results show that the multi-robot system with dynamic leader-follower strategy has more probability of getting out of the woods, and also promote the survivability rate in the leader falling situation by re-selecting a leader autonomously.** *(Abstract)*

Keywords-leader selection; formation control; affection model; multi-robot system

I. Introduction

As a specific form of multi-agent system (MAS), the cooperative control and consensus problem is focused due to its wide applications in system biology, control engineering and social science [1, 2].

Generally, MAS may suffer from the lack of planning since it consists of numbers of equal members. Thus a leader-follower strategy was introduced to programming the high level behaviors like formation control and target tracking. The controllability problem in the structure of the MAS with leader-follower strategy was considered by several research groups [3-6].

Although some of the remarkable achievements about the leader selection strategy have been reported from the state convergence point of view [5-7], they tried to accelerate the convergence rate or reduce convergence errors by determining the distribution of leaders. Different from the state convergence in the MAS, the robots may suffer from the disturbance with uncertain probability distribution in a strange area. Static indicators are not suitable for measure of the time varying situation faced by the robots. When the robots are caught in a dilemma, no matter which leader is pre-selected, the fixed-leader strategy cannot guide members to go out the predicament. In addition, if the chosen leader fails in the process of moving, the entire team will stop. Some empirical studies have indicated that the leadership is relevant to the individual's need and temperament to a large extent[8-10]. But only a few attempts have been made to improve the performance of MRS. Therefore, we are committed to the improvement of the formation efficiency and autonomous behavior patterns, making MRS more efficient, robust and easy to implement.

In human society, a very common phenomenon is that the feelings of human have a major impact on their behaviors, decision making, interaction etc. [11]. Their feelings about the environment affect the cooperation among robots. But so far, no ideal artificial emotion definition is generally accepted, especially when applied to the MRS. In most cases, the researchers had to creatively construct the abstract phenomenon of emotion reaction to tackle the issues of interest to them [12-14]. Recently, subjective and intuitive human concepts were applied to the robot guidance by introducing the internal state variable, which was obtained via fuzzy inference system, into the emotion model [15]. Salichs and Malfaz proposed a decision-making system based on drives, motivation and artificial emotions to meet the internal demand of the agent [16]. Nozawa et al. [17] divided the emotion into efficacy and stimulation, and put forward an emotion driven robot dynamic model. In their works, robots searched and avoided obstacles according to several given behavior rules. Lee-Johnson and Carnegie introduced artificial emotions into the mobile robot in order to improve its adaptive performance for navigation tasks [13].

In this paper, we propose an affection-based dynamic leader selection strategy (ADLSS) to switch the leader autonomously and increase the probability of robots out of the woods when team is in dilemma or the leader fails. Simulation results demonstrate the effectiveness and robustness of the proposed model.

The rest of this paper is organized as follows: Section II

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presents a brief introduction about behavior based formal control model. Inspired by the artificial affection mechanism, a self-adaptive leader selection strategy is given in Section III. Section IV analyses some details achieved from simulations. The work ends up with the conclusion and future work is given in Section V.

II. FORMATION CONTROL MODEL

In this section, we would like to introduce a robot formation structure according to the behavior-based control. A leader-follower strategy is introduced to maintain a specific shape and guide the robots to the destination.

A. Problem Statement

The main task of formation control is to form a specific shape satisfying several constrains and drive the robots move toward the target position [18]. During this process, only the leader knows where the target is and other robots, followers, follow the leader in a certain distance and angle. All robots should be able to detect and avoid the obstacles via embedded sensors.

In addition, there are also some more general model assumptions required to carry out. Each robot, marked as a little circle, can be characterized by three main features: 1) The minimal distance between the robots is $d_{\min}$, which is used to indicate the size of the robots; 2). The head direction, θ_i ($\theta_i \in [-\pi, \pi]$), relying on an arbitrary but fixed global reference system, represents the direction of its faces; 3) The velocity v_i, which is defined only in the heading direction. The positive means that the robot move forwards, on the contrary, the negative means moving backwards.

B. Formation Description

Adopting the leader-follower strategy when build the formation [6], we give an example of V-type formation with five robots as shown in Fig. 1. $R1$ is defined as the global leader. $R2$ and $R4$ follow $R1$ directly; $R3$ and $R5$ follow their team mate $R2$ and $R4$, respectively, and accordingly follow $R1$ indirectly. Since only the followers take the responsibility to maintain the formation, and the team formation can be guaranteed completely if every follower in each leader-follower pair allocated in the accurate position referred to its leader. To avoid complex communication, the readily obtained information of each robot will be used to build the formation.

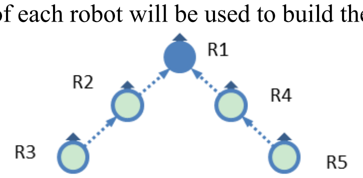


Fig. 1. An example of V-type formation. *Leader* robot is emphasized by dark color.

Considering the case of only two robots, robot i as a follower and robot j as a leader as shown in Fig. 2. In cruise, the two robots should have a consistent heading direction, and robot i always maintains a constant distance from robot j.

Kinematic models for heading direction and velocity of robot i taking robot j as a reference point are abstractly defined as follows

$$\dot{\theta}_i(\psi_i, d_{i,j}) = f_i(\theta_i, P)\,, \tag{1}$$

$$\dot{v}_i(\psi_i, d_{i,j}) = g_i(v_i, P)\,, \tag{2}$$

where θ_i stands for the heading direction of robot i, v_i stands for the velocity, ψ_i denotes the angle deviation between the i-th and j-th robot, and P is a set of parameters. To extend the function of MRS, a formation matrix is used to describe the designed formation with N robots as follows.

$$\boldsymbol{S} = \left(\boldsymbol{L}, \boldsymbol{\psi_d}, \boldsymbol{l_d}\right), \tag{3}$$

where $L_{i,d} \in \boldsymbol{L}$ is the leader's ID of robot i. $L_{i,d}$ taking zero means robot i is the global leader. $\psi_{i,d} \in \boldsymbol{\psi_d}$, and $l_{i,d} \in \boldsymbol{l_d}$ is the designed distance between the leader and the follower (See more details in [18]). The formation control aims to converge ψ_i to $\psi_{i,d}$ and v_i to v_j with a constant $d_{i,j}$ while robots are moving to the target.

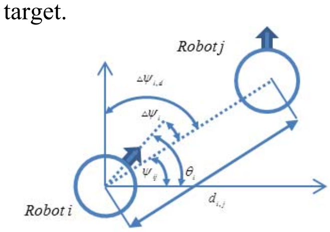


Fig. 2. Illustration of notates with two robots. Robot i is supposed to be the follower and robot j be the leader.

III. AFFECTION-BASED LEADER SELECTION MODEL

In this section we focus on proposing a dynamic leader selection model to address the local optimal problem and improve the survivability rate of MRS in the leader failure situation.

A. Concept and Model of Affection

In the real life, the leader of a group is not always fixed. When an individual is in a comfortable state, the assessment of its leader is often relatively high, at that time it more inclines to follow such a leader. When the deterioration of the living condition threats the individual, it becomes disappointed to the incumbent leader. The leader also feels guilty, even resign, because it puts the team into a dilemma. The one with more prestigious will replace the original leader and lead the team.

Analogy above phenomenon, by means of different virtual emotions, we propose a leader selection strategy, called affection-based dynamic leader selection strategy (ADLSS), to switch the leader adaptively based on the environment in which the robots stay, thereby reducing the probability of the robots being trapped in the local optimal point when they explore unknown areas. Thus the following definitions are used to simulate the psychological state of robots.

***Definition* 1. Disappointment**. The disappointment of a robot is an abstract evaluation of its statement. It increases along with the duration of a robot in a dilemma. The more disappointment there is, the intenser the individuals are to abandon the current leader and select a new leader. When the disappointment of an individual exceeds a certain threshold, followers will send a signal to the group leader to ask for a re-selection. The disappointment is calculated by the following formula within a range of $[0,1]$

$$D_i(k) = \min(D_i(k-1)e^{-1/T_i} + \delta(1-e^{-k_d(k-k_0)}),1)\,, \tag{4}$$

where T_i is the half-life variable, k_d is the integration constant and k_0 is the step when the robot i drops into a dilemma. δ takes 1 when the robot is trapped, otherwise takes 0. The equation (4) denotes that the disappointment value of robot i, D_i, eliminates as time goes on (the first item of (4)), and enhances when the robot is trapped. The second item of (4) will reach 1 if a robot trapped for a while. In such situation, the recursive calculation of D_i may beyond 1. To keep D_i in the range of [0, 1], we take a min-operation.

***Definition* 2. Abashment**. Abashment is the unique attribution of the leader robot, and it increases in line with how long the robot is stranded in the plight and the re-selection signal it receives. The abashment with the range of $[0,1]$ is denoted as follows

$$A_i(k) = \min(A_i(k-1)e^{-1/T_i} + \frac{1}{q}[\delta(1-e^{-k_a(k-k_0)}) + \frac{N_i}{N}],1) \tag{5}$$

where N is the total number of the robots, N_i is the number of the unsatisfied signals the leader received from the followers at the current time, and q is the scaling factor to regulate the value of A_i. The rest parameters and operations are the same as those mentioned above. The leader robot abandons the leadership and initiates the re-selection when the abashment exceeds the threshold.

T_i and $k_{d(a)}$ in (4) and (5) determine the rising slope of emotion values. It goes sharply or gently when $1/T_i$ and $k_{d(a)}$ increasing or decreasing. Due to the influence of these two parameters, compared with the moment when the robots fall into trouble, the MRS leader switching delayed, and this delay is essential to avoid the leader updating too fast.

By determining the current status (CS) of the robots, we can design a trigger to stimulate the affection model. The following factors are considered to estimate the status:

(1) Whether the team stays close to the target. (*Nearby*)

(2) The density of obstacles around the robot. (*Density*)

(3) The velocity of the robot, v_i.

Wherein Factors (1) and (2) describe the state of the environment obtained from the sensing system. Factor (3) can be easily read by reading the axle laser encoder. We normalize the factors (2) and (3) as follows to ensure the calculation results in the same order of magnitude

$$I_{density,i} = \begin{cases} N_{obs} / N^*_{obs}\,, & if\ N_{obs} < N^*_{obs} \\ 1 & , otherwise \end{cases} \tag{6}$$

$$I_{v,i} = v_i / v_{\max} \tag{7}$$

where N^*_{obs} is the predefined maximal number of obstacles in the sensing range of a robot, $v_{\max}$ is the maximum velocity permitted by the robot. The CS can be characterized as

$$CS_i = (1 - I_{nearby})(\omega I_{density,i} + (1-\omega)I_{v,i})\,, \tag{8}$$

where I_{nearby} is a Boolean value and $\omega \in [0, 1]$ is a regulation factor to balance the effects of the obstacle density and deceleration. The high value of CS signifies a difficulty and dilemma.

The leader re-selection process of the MRS based on affection trigger can be represented by the flowchart in Fig. 3. When travelling, robots calculate their own affections as one of their properties. When they are in a complex terrain, the CS will overpass the threshold defined in advance. These two affections are triggered at that time. When the global leader's abashment value exceeds the threshold, the re-selection occurs. The new leader and movement strategy will be utilized to help the team get out of the trouble.

Here we give a simple example that all robots take global leader as a reference substance. To structure the formation illustrated in Fig. 1, the formation matrix is defined as

$$\boldsymbol{S}_{tri} = \begin{pmatrix} 0 & 0 & 0 \\ 1 & \pi/4 & 4 \\ 1 & \pi/4 & 8 \\ 1 & -\pi/4 & 4 \\ 1 & -\pi/4 & 8 \end{pmatrix}. \tag{9}$$

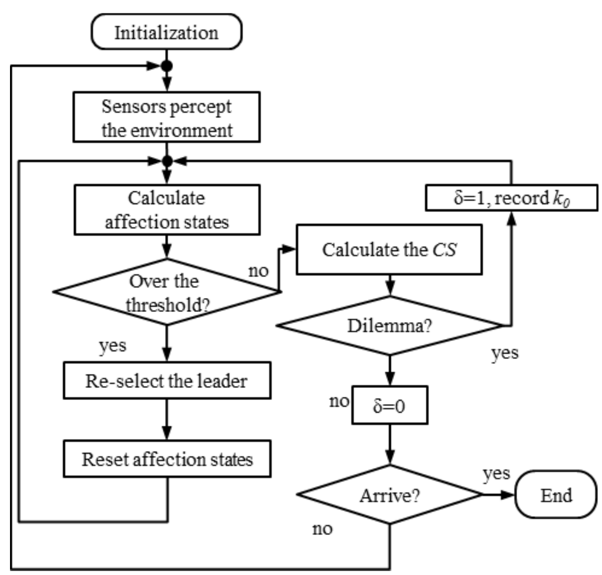


Fig. 3. The flowchart of the affection model.

A new leader is selected whose CS value is the lowest. This kind of simple strategy is only used to demonstrate how the ADLSS works. More complex formation generation algorithm, such as the minimal distance or shortest time cost strategies, will be discussed in the following work.

B. Parameters Analysis

When the parameters take different values, the proposed affection model will be affected, thereby affecting the performance of the MRS. When the re-selection frequency is too high, the operating costs increase sharply, and meanwhile, after switching the leader, followers have to change their travel directions in order to track the position of the new leader. These disadvantages usually result in the entire team deviating from the target point. The over switching in the MRS will also make the team stagnate or wander back and forth around a certain position. The impacts of key parameters are analyzed to ensure that the leader switching frequency reasonably.

One of the vital parameters is the scaling factor q in Eq. (5), which affects the accuracy of abashment value. If the value of e is too small, it will result in that the abashment value always equals 1. On the contrary, an overlarge value of q causes a long-lasting lower abashment compared with the threshold, as a result it cannot trigger the re-selection operation. Since the trigger of the leader re-selection must happen in the rising edge of abashment curve, and the trigger threshold is less than 1, the update model (5) can be rewritten as the following form

$$A_i(k) = \frac{1}{q(1-B)}[(1-e^{-k_a(k-k_0)}) + N'] , \tag{10}$$

where $B = e^{-1/T_i}$, $N' = N_i / N$. The calculation formula of q is

$$q = \frac{1}{A_{i,trg}(1-B)}[(1-e^{-k_a(k-k_0)}) + N'] . \tag{11}$$

Considering the situation that a re-selection happens when over 3/4 members in the team sending despair signal to the leader with its abashment over 0.6, the scaling factor q equals 3.189 according to (11). Other parameter values are listed in Table I.

TABLE I
VALUES OF KEY PARAMETERS

Parameter	$T_{i,d}$	$T_{i,a}$	k_d	k_d	N^*_{obs}	Th_{status}	$A_{i,trg}$
Value	100	2	0.01	0.0008	7	0.6	0.6

IV. SIMULATION RESULTS

In this section, we will illustrate our main results by comparing the fixed leader strategy with the proposed dynamic leader selection strategy in formation error, time-cost, target arriving ratio, survivability and other aspects via computing simulations. Trajectories of robots will be given in the form of curves in the x-y plane in each experiment.

Referring the citations [19] and [20], the performance of the formations contains two parts. First, the famous alignment is defined by

$$\alpha = \frac{1}{N}\sqrt{(\sum_{i=1}^{N}\cos\theta_i)^2 + (\sum_{i=1}^{N}\sin\theta_i)^2} . \tag{12}$$

It is employed to measure the extent in which the robots are moving in the same direction. When all the robots face the same direction, α gets 1, and it decreases when the directions changes from ordered to chaotic. The extent of formation error [18] is defined as the mean square error of all robots to the corresponding virtual locations. It is formulized as

$$d = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_l - x_i - l_{i,d}\cos\eta)^2 + (y_l - y_i - l_{i,d}\sin\eta)^2} \tag{13}$$
$$\eta = \theta_l - \psi_{i,d}$$

where x_l , y_l and θ_l represent the global leader's position in *X-Y* plot and the heading direction, respectively. x_i , y_i and $\psi_{i,d}$ are respectively the position and designed difference between heading direction and global leader's position of robot i. Other variables such as $l_{i,d}$ and $\psi_{i,d}$ can be seen as parameters in a new formation matrix where each robot takes the global leader as a reference point as shown in Fig. 4.

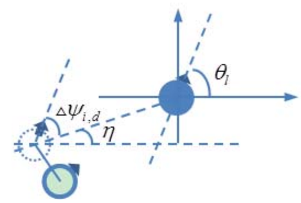


Fig. 4. The illustration of formation error calculation. The darker circle denotes the global leader robot, and the circle with dot line is the virtual location where the robot i should be. Formation error for robot i is the Euclidean distance between the actual position and the virtual one.

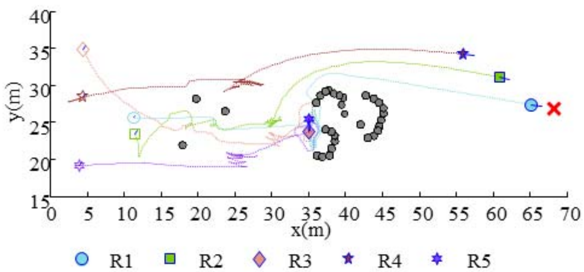
In the following discussion, if the formation error d is lower than a certain threshold which is taken as 10% of the designed distance between robots in [18], we treat the MRS as being satisfied with the accuracy requirement of the designed formation.

A. Robustness to Environmental Disturbances

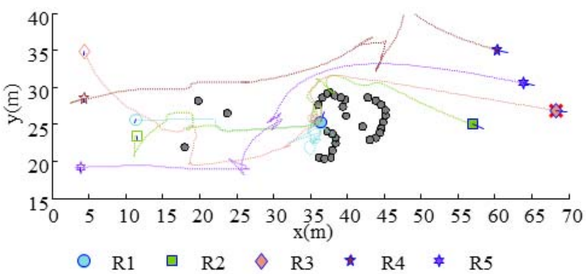
To evaluate the MRS's robustness to external environmental disturbances, we would like to build a complex map as shown in Fig. 5. with all robots locating in the left of the map. The robots need to first go through the sparse obstacles area which is designed to test the normal obstacle avoiding ability. Then, a meticulous designed obstacles area (denoted as gray circles) tries to trap the robot. Figs. 5(a) and (b) demonstrate the moving traces with and without the ADLSS in the complex map. The position errors and consistency of angle are given in Figs. 6 and 7, respectively.

As can be seen from Fig. 6, the performances of the MRS with or without the ADLSS have no difference when obstacles are distributed sparely, but will vary when dealing with the trapping area. Two curves coinciding with each other from the beginning to about 11s in Figs. 6. Figure 7 shows the secondary evidence of this phenomenon. This is because in the spare obstacle area, the robots perceive a well status, and re-selection operation has not been triggered. When they move into the area with meticulous distributed obstacles, the formation error of fixed leader model presents a periodical variation. It also shows the same frequency oscillation in consistency of the angle at the same time, which means that most robots are parked but a few stand around, which is mainly caused by some local minima point. The MRS with the ADLSS performs a lower consistency of angle in the trapping area.

Switching leader process offers more direction selection to gain a greater probability of escape from the trapping area. During the whole experiment process, three times of leader re-selection are occurred and the corresponding leader switching process is as shown in Fig. 8.

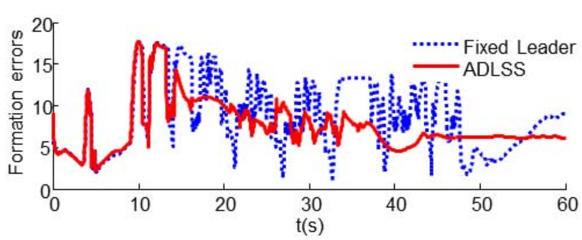


(a)



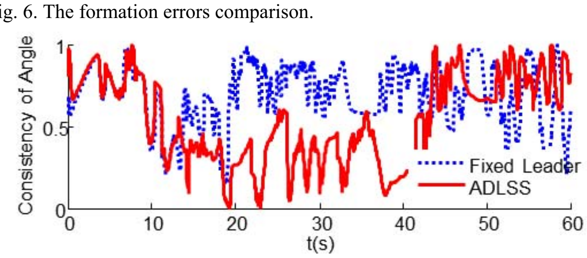
(b)

Fig. 5. The trajectory of the MRS. (a) Robots move without changing leader. (b) Robots move with the ADLSS.



(a)

Fig. 6. The formation errors comparison.



(b)

Fig. 7. The consistencies of angles comparison.

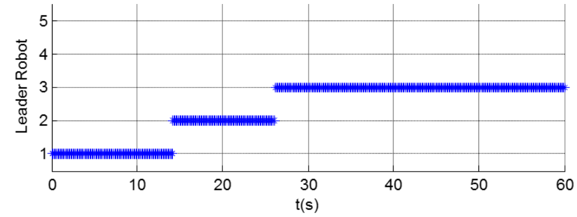


Fig. 8. Illustration of leader switching with the ADLSS

To verify the efficiency and superiority of ADLSS, we carry on 40 times of repeat experiments with these two models. In each experiment, all robots are initialized randomly, and the simulation time is limited in 100s. We also employ a t-test to verify if there exists a statistically significant difference between these two methods. H=0 means they have no statistic difference, H=1 on the contrary. The reaching probability and time-cost are calculated and compared in Table II.

TABLE II
PERFORMANCE COMPARISION

	Fixed Leader	ADLSS	H	P
Arriving Ratio	0.39 ± 0.27	0.43 ± 0.28	1	0.0064
Arriving Time	60.68 ± 19.13	56.53 ± 15.01	1	0.0035
Absence Ratio	30%	28.75%	-	-

*Choose the significance level as 0.05.

In Table II, the arriving ratio is calculated as the number of arrived robot divided by the total number of robots and the absence ratio is the percentage of experiment times in which no robot arrives the target. It shows that the robot team with the ADLSS has a decrease in absence ratio, which means a lower probability of being trapped in the environment. The comparison of time-costs to arrive the target also shows the strong ability to get out of the woods with proposed model. The t-test results also support that the improvement of the proposed method is significant.

It can conclude that the MRS with the ADLSS is more effective at dealing with the complicated terrain. We may draw the conclusion from the previous simulation results that the proposed algorithm has higher robustness to the environment disturbance.

B. The Survivability after Leader Failure

Another critical problem in the MRS is the survivability. Generating a formation via leader-follower strategy is weak in a calculated attack since the system will break down if the leader is under attack. Although every robot knows the target position the system can drop into chaos since they don't know whom they should follow. Thus we design an experiment to test if the proposed strategy can overcome this drawback. The simulation environment is limited in a 70×25 rectangle space with several obstacles. In a MRS with 5 robots, the current global leader (marked as blue circle) stops at 5s after it starts travelling. And the second leader, which is marked as a purple star in this issue, malfunctions at 20s. The moving traces and the corresponding leader switching process are provided in Fig.

9 and 10.

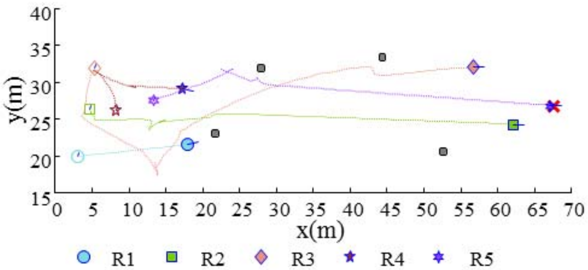


Fig. 9. Trace evolution for the MRS with leader failure.

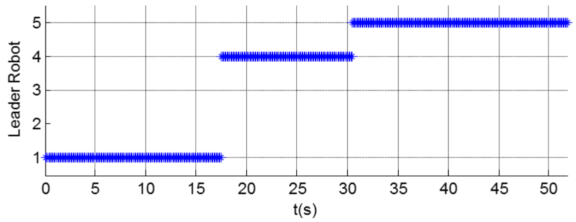


Fig. 10. Illustration of leader switching with the ADLSS.

It can be observed that the team can reselect the global leader autonomously when the failure happens. And in this way they keep moving towards the target.

In addition, the leader switching timing and the leader failure do not happen at the same moment. This is because the disappointment of team members cumulates over time when the global leader is in failure. As we discussed before, this delay is necessary to prevent over switching.

V. CONCLUSION AND FUTURE WORK

In this paper, we propose a self-adaptive dynamic leader selection strategy based on two kinds of virtual affections and apply it to solve the local optimal problem in the formation control of the MRS. The proposed algorithm changes the leader autonomously to improve the probability of getting out of the woods when the group falls into trouble. More interestingly, it doesn't require additional information to notify the team members to initiate a selection when the leader has a mechanical failure. Robots will select a new leader according to their affection states and continue to fulfill the mission. Plenty of simulation results demonstrate the effectiveness and robustness of the proposed model.

In this work, the definition of the robot's current status is rough, and the followers' behaviors after leader re-selection have not been conducted yet. The more reasonable cognition method and the optimized following strategies of the followers are the focuses of our future research. In addition, the dynamic leader selection for multi-target tracking is on our schedule.

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