

Design of Interval Type-2 Fuzzy Logic Controllers for Flocking Algorithm

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Abstract—This paper presents a novel interval type-2 fuzzy logic control architecture for flocking system when the system has noisy sensor measurements. The traditional type-1 fuzzy logic controller (FLC) using precise type-1 fuzzy sets cannot fully model and handle the uncertainties of sensor data. However, type-2 FLC using type-2 fuzzy sets with a footprint of uncertainty (FOU) produces better performances under noisy environments. In this paper, therefore, we present a reactive control architecture for flocking algorithm that is based on interval type-2 FLC to implement the flocking behaviors consisting separation, obstacle avoidance, and velocity matching behaviors. The type-2 based control system could cope with the uncertainties of noisy sensor measurements and resulted in good performances that outperformed the type-1 FLC.

Keywords—Type-2 fuzzy logic controller (FLC), flocking algorithm, reactive control, multi-agent systems

I. INTRODUCTION

In 1970s, the concept of type-2 fuzzy logic system (FLS) was first introduced by Zadeh [1]. Compared to traditional type-1 fuzzy sets which have membership functions that are precise, the type-2 fuzzy sets are described by membership functions that are themselves fuzzy. Thus, type-2 FLS can be successfully used to model and handle data uncertainties in many applications. However, the type-2 FLS has some difficulties in 1) characterization of type-2 fuzzy sets; 2) performing operations; 3) inferencing, and 4) obtaining a defuzzified value which is type-0 set from the output of a type-2 inference engine which is type-2 fuzzy set [2]. After the publication of Karnik and Mendel [3] which introduces some new concepts to overcome the difficulties stated above, a lot of papers up to recently have been published about type-2 FLS [4]-[6].

Fuzzy logic controllers (FLCs) have been successfully implemented for reactive control of robots. However, most of the researches in robot control fields are based on the traditional type-1 FLC [7]-[10]. Recently, several researchers have applied type-2 FLC to mobile control. For instance, Hagrass [4] applied type-2 FLS to mobile robot control in real-time for changing and dynamic environments, and the type-2 FLC resulted in good control responses compared with the type-1 FLCs. Martinez *et al.* [5] have investigated the usage of

tuning technique to tune the parameters of type-2 FLC for mobile robots by using genetic algorithms.

There have been many studies for flocking behavior of multi-agent systems. For the simulation of flocking birds, Reynolds [11] introduced three heuristic rules that lead to the creation of the first computer animation model of flock. The three rules are for cohesion, separation, and alignment. In Reynolds' model, there is no leader in the flock and each bird has a local control strategy. After that, several researches on flocking motion applied the heuristic rules used in Reynolds' model to their algorithms. Olfati-Saber [12] designed artificial potentials based on graph theory to form a lattice-shape formation of robots and Bennet and McInnes [13] proposed bifurcating potential field by considering pattern formation and reconfigurability in flocking system. Moshtagh and Jadbabaie [14] proposed a method that considered velocity alignment in a group of kinematic nonholonomic robots. By analyzing the velocity vectors on a circle or sphere, they proposed a distributed control law that results in an agreement of velocity vectors and flocking. Recently, fuzzy logic based approaches to flocking algorithm are developed. Gu and Hu [15] proposed a fuzzy logic solution to the separation control problem by applying Takagi-Sugeno (TS) rules and Gaussian membership functions. Yu *et al.* [16] designed an attractive/repulsive potential function based on fuzzy logic.

To date there have been many studies on type-1 FLC for multi-robot and flocking control [15], [16], whereas few studies on control of flocking robots with considering uncertainty in environments are found in the literatures. There is one paper written by Gu and Hu [15] which discusses robustness of flocking algorithm with bounded random noise, but it has limitations in handling the noise because they used type-1 fuzzy sets.

In this paper, we use the interval type-2 fuzzy logic to design controllers for flocking algorithm. The controllers enable robots to behave toward flocking by Reynolds' model. The robots used in this paper are modeled by second order dynamical system which is fully actuated. The simulation results of type-2 FLCs are presented and their results are compared with the results of type-1 FLCs to verify the robustness of type-2 FLCs with noisy sensor measurements.

The rest of the paper is organized as follows. Section II presents a flock model for robots with second order dynamical system. Section III proposes interval type-2 FLCs for flocking algorithm. The simulation results of the proposed type-2 FLCs are provided and discussed in Section IV. Finally, conclusions are presented in Section V.

II. FLOCK MODEL

A. Robot Dynamics

Let us consider a group of n robots (or particles) modeled by second order dynamical system with the following equation of motion:

$$\begin{aligned}\dot{q}_i(t) &= p_i(t) \\ \dot{p}_i(t) &= u_i(t)\end{aligned}\quad (1)$$

where $q_i(t), p_i(t) \in \mathbb{R}^m$ are the position and velocity vectors of robot i , respectively, and $u_i(t) \in \mathbb{R}^m$ is a control vector which will be introduced later. It is assumed that all robots can communicate with each other and are fully actuated. The states of all n robots can be joined into vectors $q=[q_1, \dots, q_n]^T \in \mathbb{R}^{mn}$, $p=[p_1, \dots, p_n]^T \in \mathbb{R}^{mn}$, and $u=[u_1, \dots, u_n]^T \in \mathbb{R}^{mn}$.

Let $q_d(t)$ and $p_d(t)$ be the desired position and velocity states for the group center. To track the desired position and velocity, a state feedback control law is applied to all robots in a group as follows:

$$u_i^{track} = -c_1(q_i - q_d) - c_2(p_i - p_d) \quad (2)$$

where c_1 and c_2 are the feedback gains, which can be represented by n -dimensional diagonal matrices. Then, the collective dynamics of a group of robots with the control input $u^{track} = [u_1^{track}, \dots, u_n^{track}]^T \in \mathbb{R}^{mn}$ can be represented in the following form:

$$\begin{aligned}\dot{q}(t) &= p(t) \\ \dot{p}(t) &= u^{track}(t).\end{aligned}\quad (3)$$

By using the control input $u^{track}(t)$, all robots belonging to the same group move to follow the desired trajectory.

The center of the group can be represented by the average of all states as follows:

$$q_c = \frac{1}{N} \sum_{i=1}^N q_i(t), \quad p_c = \frac{1}{N} \sum_{i=1}^N p_i(t). \quad (4)$$

From (1)-(4), the control input of the group center has the following form:

$$u_c^{track} = -c_1(q_c - q_d) - c_2(p_c - p_d). \quad (5)$$

Then, the dynamics of the center of the group can be represented by:

$$\begin{aligned}\dot{q}_c(t) &= p_c(t) \\ \dot{p}_c(t) &= u_c^{track}(t).\end{aligned}\quad (6)$$

B. Definition of Flocking Model

The flocking model was proposed by Reynolds [11] in 1986 for computer simulation of flocking behavior like flocking birds. The flocking model consists of the following three heuristic rules:

- 1) *Cohesion behavior*: attempt to stay close to nearby flockmates
- 2) *Separation behavior*: avoid collisions with nearby flockmates
- 3) *Velocity matching behavior*: attempt to match velocity with nearby flockmates

In this paper, not only the three rules of Reynolds but also obstacle avoidance behavior is designed through three interval type-2 FLCs in order to achieve the flocking behavior in environments with obstacles. Here we use interval type-2 fuzzy sets to design the FLCs, and then the robustness of the internal type-2 FLCs is tested with noisy sensor measurements. The three FLCs are designed to achieve cohesion-separation, velocity matching, and obstacle avoidance behaviors respectively.

III. TYPE-2 FUZZY LOGIC CONTROLLERS (FLCs) FOR FLOCKING ALGORITHM

In developing type-2 FLC for flocking algorithm, fuzzy sets are represented by Gaussian interval type-2 fuzzy sets. In Gaussian type-2 fuzzy sets, uncertainties are associated with the value of mean or standard deviation. In this paper the fuzzy sets with uncertain mean value is considered because uniform random noise is used to test the robustness of the type-2 FLCs.

For the simulation of flocking behaviors, three FLCs corresponding to each of the flocking behaviors are designed as shown in Fig. 1. Each FLC receives a crisp input value and then produces control output u_i^{sep} , u_i^{vel} , and u_i^{obs} . To determine the movement of each robot in the next step, the sum of the control outputs including u_i^{track} in (2) is used as u_i in (1). Thus, the total control function u_i is

$$u_i = u_i^{sep} + u_i^{vel} + u_i^{obs} + u_i^{track}. \quad (7)$$

In the rest of this section, three FLCs for each behavior in flocking algorithm based on interval type-2 fuzzy sets will be described to verify the robustness of the interval type-2 FLCs in the presence of uncertainty.

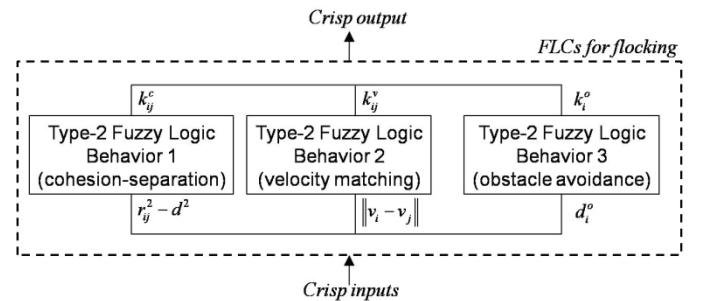


Fig. 1. Type-2 FLCs for flocking

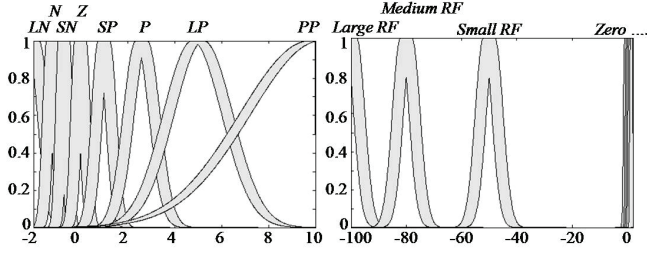


Fig. 2. Input (left) and output (right) membership functions for cohesion-separation behavior

A. Type-2 FLC for Cohesion-Separation Behavior

The FLC for cohesion-separation behavior make the robots in a group gather together around the group center while keeping robots with constant distance from others to avoid collisions with nearby robots. In order to achieve the cohesion-separation behavior, the type-1 FLC developed by Gu and Hu [15] is reformulated into an interval type-2 FLC, and it is used for cohesion-separation control. In developing the type-2 FLC for cohesion-separation control, eight type-2 Gaussian fuzzy sets which have a footprint of uncertainty (FOU) to model and handle the uncertainties of sensor data are designed as shown in Fig. 2. In the figure, the area of FOU is shaded in gray. Also eight fuzzy rules are designed as follows in a similar manner to [15]:

IF	$r_{ij}^2 - d^2$	is	LN	THEN	k_{ij}^s	is	Large RF
IF	$r_{ij}^2 - d^2$	is	N	THEN	k_{ij}^s	is	Medium RF
IF	$r_{ij}^2 - d^2$	is	SN	THEN	k_{ij}^s	is	Small RF
IF	$r_{ij}^2 - d^2$	is	Z	THEN	k_{ij}^s	is	Zero
IF	$r_{ij}^2 - d^2$	is	SP	THEN	k_{ij}^s	is	Small AF
IF	$r_{ij}^2 - d^2$	is	P	THEN	k_{ij}^s	is	Medium AF
IF	$r_{ij}^2 - d^2$	is	LP	THEN	k_{ij}^s	is	Large AF
IF	$r_{ij}^2 - d^2$	is	PP	THEN	k_{ij}^s	is	Very Large AF

where r_{ij} is the distance between robot i and robot j and d is desired distance between two robots. The control function of the robot i which include all effects from all robots in the group is

$$u_i^{sep}(t) = -\sum_i^n k_{ij}^s (q_i - q_j) \quad (8)$$

where $k_i^s = [k_{i1}, \dots, k_{in}]^T \in \mathbb{R}^n$ is the fuzzy output vector. The control function acts as a potential function on the robots, i.e. if the fuzzy input $r_{ij}^2 - d^2$ becomes negative value, then repulsive force (RF) acts on the robots; on the contrary, if the value becomes positive, then attractive force (AF) acts on the robots. In this manner, robots in a group can congregate without collisions with each other.

To measure the degree in which robots take the cohesion-separation behavior, we introduce the following *potential energy function*:

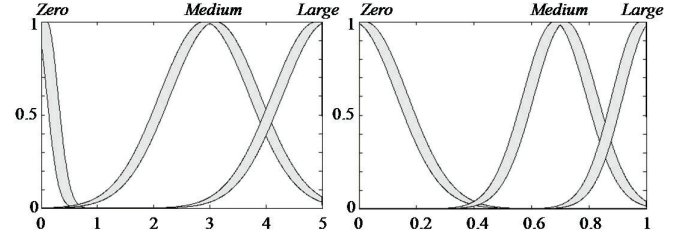


Fig. 3. Input (left) and output (right) membership functions for velocity matching behavior

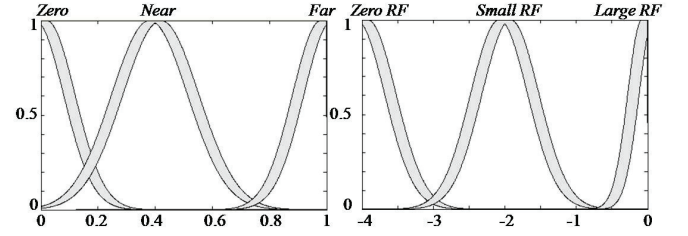


Fig. 4. Input (left) and output (right) membership functions for obstacle avoidance behavior

$$E(q) = \sum_i^n \sum_{j=i}^n \psi(\|q_i - q_j\| - d) \quad (9)$$

where $\psi(x) = x^2$. With this potential energy function, if the value becomes smaller, the flocking of robots is more stable.

B. Type-2 FLC for Velocity Matching Behavior

The FLC for velocity matching behavior is designed to align the velocity of each robot considering the others. The FLC receives only one crisp input value $\|v_i - v_j\|$ to determine fuzzy output value k_{ij}^v . For the FLC, we represented the input and output fuzzy membership functions as *Zero*, *Medium*, and *Large* with FOU as shown in Fig. 3, and three simple fuzzy rules are designed as follows:

IF	$\ v_i - v_j\ $	is	Zero	THEN	k_{ij}^v	is	Zero
IF	$\ v_i - v_j\ $	is	Medium	THEN	k_{ij}^v	is	Medium
IF	$\ v_i - v_j\ $	is	Large	THEN	k_{ij}^v	is	Large

The control function of robot i for velocity matching behavior is

$$u_i^{vel}(t) = -\sum_{j=i}^n k_{ij}^v (v_i - v_j) \quad (10)$$

where $k_i^v = [k_{i1}, \dots, k_{in}]^T \in \mathbb{R}^n$ is the fuzzy output vector. With this control function, a robot tends to align its velocity with other robots which have large velocity difference with it.

To measure the degree of velocity alignment, we use the following *deviation energy function*:

$$V(p) = \sum_i^n \sum_{j=i}^n \psi(\|p_i - p_j\|). \quad (11)$$

If the velocity $p_i(t)$ reaches an average velocity of all the robots, their headings and speed will be the same. Thus, the deviation energy function $V(p)$ becomes zero.

C. Type-2 FLC for Obstacle Avoidance Behavior

The obstacle avoidance behavior is needed for safe navigation in environments with obstacles. To design the type-2 FLC, we assume that there is one static obstacle and each robot has a range sensor which can detect the range from a robot to the obstacle when the obstacle is located within the r_{max} maximum detectable range of the sensor. Under this assumption, the range sensor value is represented by three interval type-2 fuzzy sets; *Zero*, *Near*, and *Far*; and the output fuzzy sets *Zero RF*, *Small RF*, and *Large RF* as shown in Fig. 4. The three simple fuzzy rules are designed as follows:

IF d_i **is** *Zero* **THEN** k_i^o **is** *Zero RF*
IF d_i **is** *Near* **THEN** k_i^o **is** *Small RF*
IF d_i **is** *Far* **THEN** k_i^o **is** *Large RF*.

The control function of robot i for obstacle avoidance behavior is as follows:

$$u_i^{obs}(t) = -\sum_i^n k_i^o (q_i - q^{obs}) \quad (12)$$

where k_i^o is the fuzzy output and q^{obs} is the position of obstacle. If the distance between the robot and the obstacle becomes smaller, then the robot feels large repulsive force from the obstacle. Thus, the type-2 FLC results in obstacle avoidance behavior.

IV. SIMULATION RESULTS AND DISCUSSIONS

In this section, we present several simulation results of interval type-2 FLCs for flocking and compare their results with those of type-1 FLCs. In the simulations, a group of 10 robots in 2-D (i.e. $m=2$) is used, and all of them are networked with each other, i.e. the locations and velocity vectors of all robots are available to any robots belonging to the group for cohesion-separation and velocity matching behaviors.

For simulations, the robots are initially located randomly within a square of $[-2.5\text{m}, 2.5\text{m}]$ and $[-2.5\text{m}, 2.5\text{m}]$ in X and Y directions, respectively. The velocities are initially set randomly in the interval of $[-1\text{m/s}, 1\text{m/s}]$. The following parameters remain fixed throughout all simulations: $d=0.3\text{m}$ for the cohesion-separation behavior, $r_{max}=1\text{m}$ for the obstacle avoidance (range sensor), $c_1=1$ and $c_2=1$ for tracking a given reference trajectory. The reference trajectory which should be followed by the center of the flock is given by a straight line represented by

$$q^d = [0.5t \ 0]^T. \quad (13)$$

A. Tracking reference trajectory without obstacles

In the first test, the type-1 and type-2 FLCs for flocking are tested without obstacle avoidance behavior. To test the

robustness of the FLCs, uniform random noise which produces data points that have the standard uniform distributions is applied to the measurements of range and velocity.

Figs. 5-6 show robot trajectories controlled by type-1 and type-2 FLCs respectively. As shown in the figures, the robots are initially located at random, and congregate around a center of the flock. As time goes on, the flocking becomes stable, and

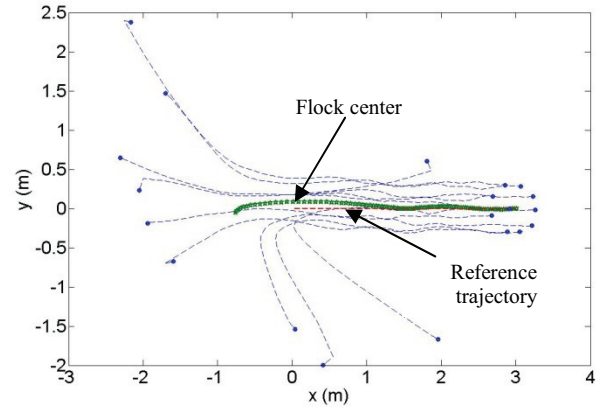


Fig. 5. Trajectories of robots by type-1 FLCs

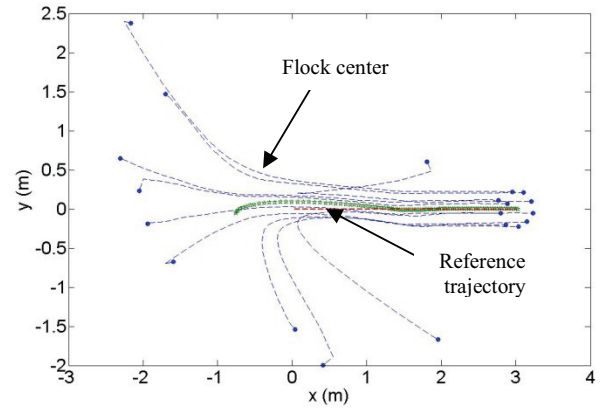


Fig. 6. Trajectories of robots by type-2 FLCs

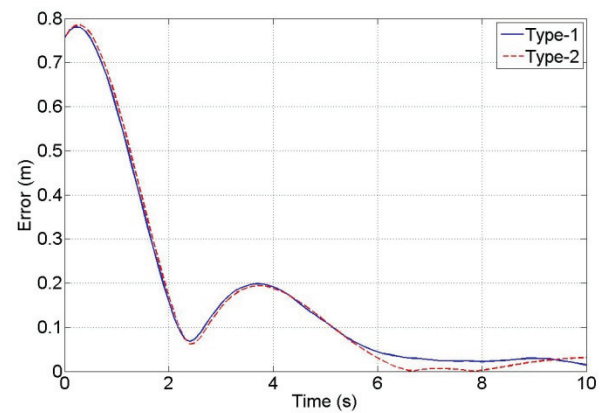


Fig. 7. Tracking error of the flock center

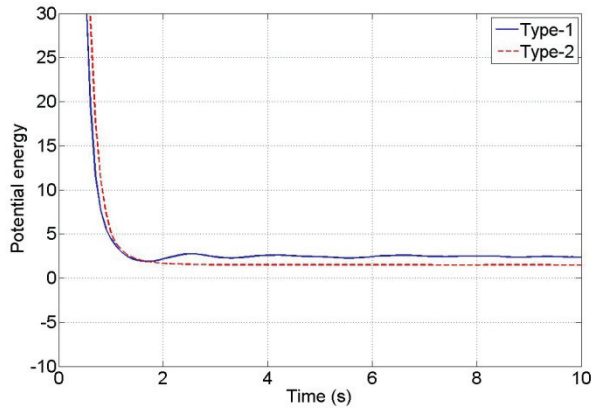


Fig. 8. Potential energy of flocking robots

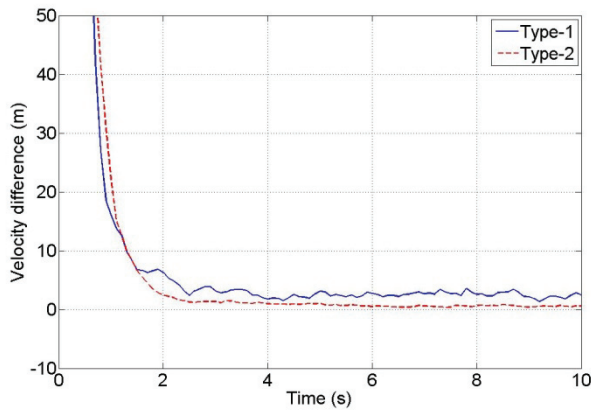


Fig. 9. Degree of velocity difference between robots

its center tracks the reference trajectory q_i^d . As shown in Fig. 5, the type-1 FLC-based cohesion-separation and velocity matching behaviors produce wobbling paths in tracking the reference path. In contrast to the type-1 FLCs, the type-2 FLCs produce smooth paths during flocking even though noisy sensor measurements are used as shown in Fig. 6. Fig. 7 shows the errors between the reference path and the center of flock trajectory. Fig. 8 shows that the potential function of type-2 have lower energy level compared with that of type-1. Also, considering the degree of velocity difference of type-1 and type-2, we can find that the type-2 shows not only lower degree but also smoother than type-1 as shown in Fig. 9. As can be seen in the results, the type-2 FLCs show robust performances under noisy environments compared to the type-1 FLCs.

B. Tracking reference trajectory with static obstacle

In the second test, the FLCs for the total flocking behaviors including obstacle behavior are tested, where the range sensors for detecting obstacles are noisy. For obstacle avoidance behavior, we assume that there is a static obstacle modeled by single point (i.e. no volume) located at $q^{obs} = (3m, 0.3m)$. Figs. 10-11 show obstacle avoidance behaviors of type-1 and type-2 during flocking. As seen in the figures, the type-2 FLCs

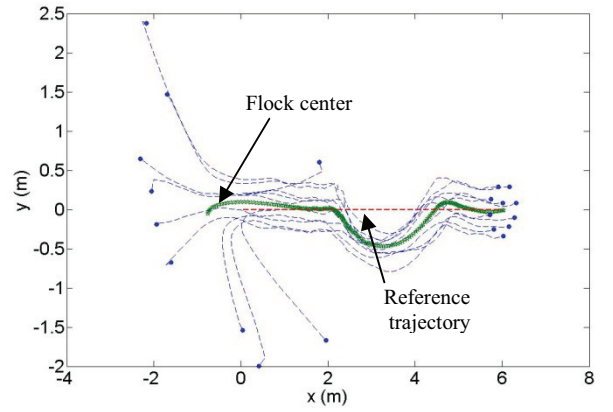


Fig. 10. Trajectories of robots by type-1 FLCs

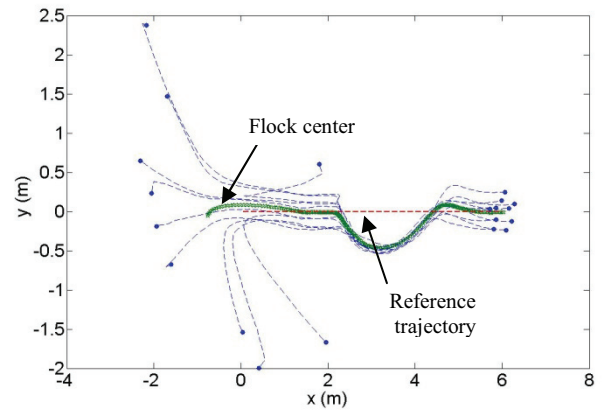


Fig. 11. Trajectories of robots by type-2 FLCs

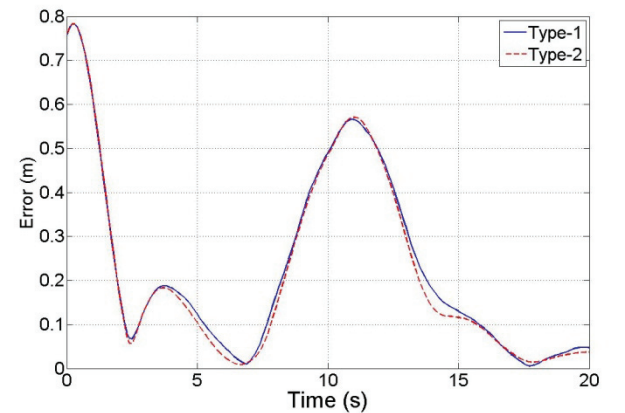


Fig. 12. Tracking error of flock center

perform obstacle avoidance more smoothly than the type-1 FLCs, when robots detect an obstacle. Fig. 12 shows that the tracking error of the type-2 show slightly better performance than type-1. With respect to the potential energy, the type-2 show lower level of potential energy than the type-1 as shown in Fig. 13. Also, considering the degree of velocity difference, we can find that the value of the degree of robots controlled by

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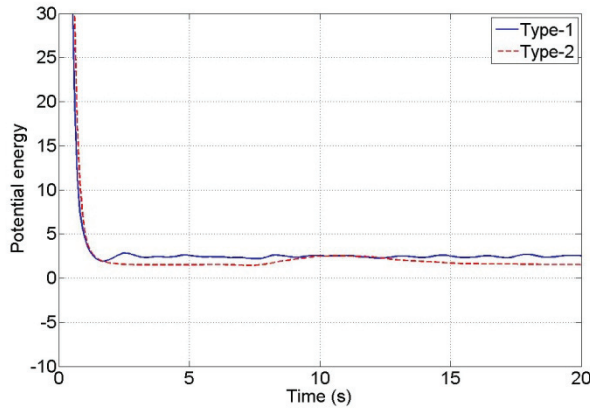


Fig. 13. Potential energy of flocking robots

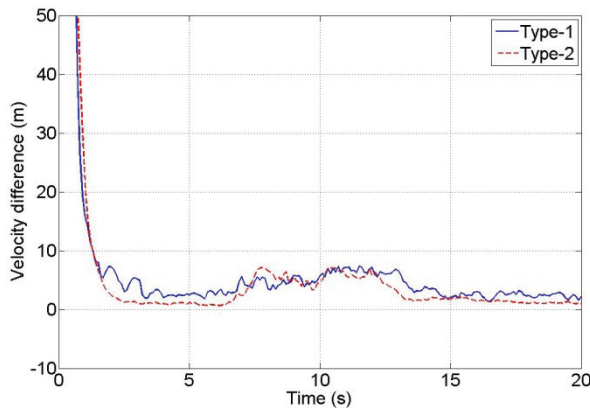


Fig. 14. Degree of velocity difference between robots

the type-2 FLCs shows better performance than the type-1 FLCs as shown in Fig. 14.

V. CONCLUSIONS

In this paper, we presented interval type-2 FLCs for flocking behaviors of robots which are modeled by the second order dynamical system, and its simulation results are compared to the type-1 FLCs with noisy sensor measurements. For flocking simulation, we proposed a structure composed of the three FLCs corresponding to flocking behaviors which consist of three components: cohesion-separation, velocity matching, and obstacle avoidance behaviors. From several simulations, we conclude that the interval type-2 FLCs are robust under uncertainties and that they resulted in better control responses than type-1 FLCs. As the use of interval type-2 FLC enables to model and handle the uncertainties effectively, the suggested FLC could provide robust performance on systems with uncertainties.