CHIN. PHYS. LETT. Vol. 28, No. 4 (2011) 040503

Stable Flocking of Multiple Agents Based on Molecular Potential Field and Distributed Receding Horizon Control *

ZHANG Yun-Peng(张云鹏)[1,2], DUAN Hai-Bin(段海滨)[1,2**], ZHANG Xiang-Yin(张祥银)[2]

[1]*State Key Laboratory of Virtual Reality Technology and Systems, Beihang University, Beijing 100191*
[2]*Science and Technology on Aircraft Control Laboratory, Beihang University, Beijing 100191*

(Received 31 March 2010)

A novel distributed control scheme to generate stable flocking motion for a group of agents is proposed. In this control scheme, a molecular potential field model is applied as the potential field function because of its smoothness and unique shape. The approach of distributed receding horizon control is adopted to drive each agent to find its optimal control input to lower its potential at every step. Experimental results show that this proposed control scheme can ensure that all agents eventually converge to a stable flocking formation with a common velocity and the collisions can also be avoided at the same time.

PACS: 05.65.+b, 45.50.−j, 45.50.Dd DOI: 10.1088/0256-307X/28/4/040503

Flocking is a form of collective behavior of a group of interacting agents with a common group objective.[1] The most important feature of flocking motion is that the agents only have local interactions. That is, one agent can only obtain the position and velocity information of several neighboring flockmates. With this local information, the agent will maneuver itself following the three flocking rules of Reynolds.[2] (1) Collision avoidance: avoid collisions with nearby flockmates. (2) Velocity matching: attempt to match velocity with nearby flockmates. (3) Flock centering: attempt to stay close to nearby flockmates. Although the agents only have local interactions, the whole group will have an emergence of coordinated flocking motion. There are several kinds of control scheme which can generate stable flocking motion.[1,3–5] In Ref. [5], Tanner presents a control scheme which utilizes a combination of attractive/repulsive and alignment forces to generate stable flocking. In Ref. [3], Hettiarachchi employs a generalized Lennard–Jones (LJ) force law combined with an evolutionary algorithm to control robots moving through obstacle fields.[3]

In this work, we introduce a novel control scheme to achieve stable flocking motion for a group of agents. This control scheme is based on an artificial potential field. A stable flocking can be attained if each agent maneuvers itself to lower its potential. This is quite similar to the interactions between molecules in physics.[4] Inspired by this, a molecular potential field model, featuring with its smoothness and unique shape, is applied as the potential field function. Then the distributed receding horizon control approach is adopted with the purpose that every agent can find the optimal control input to drive itself to reach the position with lower potential. It is shown that the molecular potential field and distributed receding horizon control approach have satisfactory performance for achieving desired flocking motion.

Consider a system of N agents, where each agent is regarded as a particle with the following dynamics:[5]

$$\dot{p} = v, \qquad \dot{v} = u, \tag{1}$$

where p represents the position, v represents the velocity and u represents the control input and the state of an agent is denoted as $x = [p, v]^T$.

The distance between agents i and j is denoted as

$$r_{ij} = ||p_i - p_j||, \tag{2}$$

where $||\cdot||$ is the Euclidean norm. The desired distance between neighboring agents is denoted as R.

The maximum detecting range of an agent is denoted as $R_{\max}$, and $R_{\max} > R$. Thus an agent can only detect the agents within its detecting range. If agent j can be detected by agent i, i.e. $r_{ij} < R_{\max}$, agent j is called a neighbor of agent i. The set of all neighbors of agent i is defined as

$$N(i) = \{j | r_{ij} < R_{\max}, j \neq i\}. \tag{3}$$

In our proposed control scheme, each agent will generate an artificial potential field. The potential field obtains its unique minimum at the desired distance R. If two agents are located at the desired distance R, the potential between them will be the lowest. The agents tends to lower their potential, thus neighboring agents will regulate the distance between each other to R, while avoiding collisions at the same time. This embodies the flock centering and collision avoidance

*Supported by the National Natural Science Foundation of China under Grant Nos 60975072 and 60604009, the Program for New Century Excellent Talents in University of China under Grant No NCET-10-0021, the Fundamental Research Funds for the Central Universities under Grant No YWF-10-01-A18, Open Fund of the State Key Laboratory of Virtual Reality Technology and Systems and Beijing NOVA Program Foundation under Grant No 2007A017.

**Email: hbduan@buaa.edu.cn

rules of Reynolds.

There are several models which can be used as the potential field.[1,3–5] In this study, a molecular potential field model is applied. The approximate molecular potential field function can be expressed by[6]

$$V(r) = -\frac{A}{r^m} + \frac{B}{r^n}, \tag{4}$$

where r denotes the distance and V denotes the potential. The parameters satisfy $A > 0$, $B > 0$ and $n > m$.

In this work, we set $m = 1$ and $n = 2$, while A and B depend on the minimum point (i.e. the desired distance R) and the strength of the potential field. An example of the potential function is shown in Fig. 1.

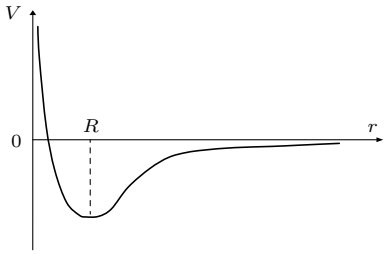

Fig. 1. An example of the molecular potential function, reaching its unique minimum at the desired distance R.

The potential between agents i and j can be defined as[5]

$$V_{ij} = V(r_{ij}). \tag{5}$$

Thus the total potential of agent i can be expressed with

$$V_i = \sum_{j \in N(i)} V_{ij} = \sum_{j \in N(i)} V(r_{ij}). \tag{6}$$

The potential of the whole system can be defined as

$$V_{\text{system}} = \sum_{i=1}^{N} V_i. \tag{7}$$

Note that the potential of the whole system V_{system} is never calculated by any agent because our control scheme is distributed. V_{system} is only calculated when analyzing the simulation results.

In order for the agents to find the optimal control input to lower its potential, a distributed receding horizon control approach is adopted. Receding horizon control (RHC) is a computer control approach, with receding optimization as its most important idea.[7] At time k, the controller predicts a control sequence from time k to time $k+p$, which can be represented by $u(k|k), \cdots, u(k+p-1|k)$. Using this control sequence and the current state $x(k)$, the state at time $k+1, \cdots, k+p$, represented by $x(k+1|k), \cdots, x(k+p|k)$ can be obtained. The fitness function at time k can be defined as[8]

$$\min J(k) = \sum_{i=1}^{p} f(x_{ref}(k+i), x(k+i|k)). \tag{8}$$

The controller will search for the optimal control sequence $u(k|k), \cdots, u(k+p-1|k)$, which makes $J(k)$ reach its minimum.

The RHC approach turns a control problem to an optimization problem. In this study, particle swarm optimization (PSO) is utilized to search the solutions of this optimization problem.

The distributed RHC approach means that each agent is equipped with a distributed receding horizon controller and can calculate its own control input with the local information obtained by itself. There is no centralized control to coordinate the whole system.

Our proposed control scheme is totally distributed. All the agents will sample, calculate, predict, optimize and implement at the same time. To describe the control scheme in detail, the working process of agent i ($i = 1, \cdots, N$) during the kth sampling interval (from time k to time $k+1$) is taken for example.

During the kth sampling interval, agent i implements the following six steps.

(1) Detection: At time k, agent i will detect all the agents within its detecting range, which are its neighbors. In this way, agent i can obtain the current state of all its neighbors $x_j(k)(j \in N(i))$ and its own current state $x_i(k)$.

(2) Prediction: Agent i predicts its control input between time k and time $k+1$, represented by $u_i(k|k)$. With this control input and its own current state $x_i(k)$, it can predict its following state at time $k+1$ $x_i(k+1|k)$. Agent i also predicts the following state of each of its neighbors at time $k+1$, denoted as $x_j(k+1|k)(j \in N(i))$. To do this, suppose that the velocities of its neighbors are unchanged between time k and time $k+1$. Then it can make a prediction as

$$\begin{aligned} p_j(k+1|k) &= p_j(k) + v_j(k) \cdot \Delta t, \\ v_j(k+1|k) &= v_j(k), \end{aligned} \tag{9}$$

where Δt is the sampling time.

(3) Calculation: After predicting $x_i(k+1|k)$ and $x_j(k+1|k)(j \in N(i))$, agent i will calculate the fitness function:

$$\begin{aligned} \min J_i(k) = M_1 V_i(k+1|k) + M_2 \sum_{j \in N(i)} &||v_i(k+1|k) \\ &- v_j(k+1|k)||, \end{aligned} \tag{10}$$

where M_1 and M_2 are the penalty factors and $V_i(k+1|k)$ is the predicted potential of agent i at time $k+1$:

$$\begin{aligned} V_i(k+1|k) &= \sum_{j \in N(i)} V(r_{ij}(k+1|k)) \\ &= \sum_{j \in N(i)} V(||p_i(k+1|k) - p_j(k+1|k)||). \end{aligned} \tag{11}$$

There are two components in the fitness function (10). The first denotes the potential of agent i, which ensures that agent i will attempt to lower its potential

by regulating the distance between itself and its neighbors to the desired distance R while avoiding collisions at the same time. The second denotes the velocity mismatch between agent i and its neighbors, which ensures that agent i will attempt to regulate its velocity to the average velocity of its neighbors.

(4) Optimization: Using optimization algorithm, agent i will find its optimal control input $u_i(k|k)$, which can make the fitness function reach its minimum.

It is assumed that these four steps can be carried out immediately by agent i at time k.

(5) Implementation: Agent i can apply this control input $u_i(k|k)$ between time k and time $k+1$.

(6) Go back to step 1 at time $k+1$ and move forward to the $(k+1)$th sampling interval.

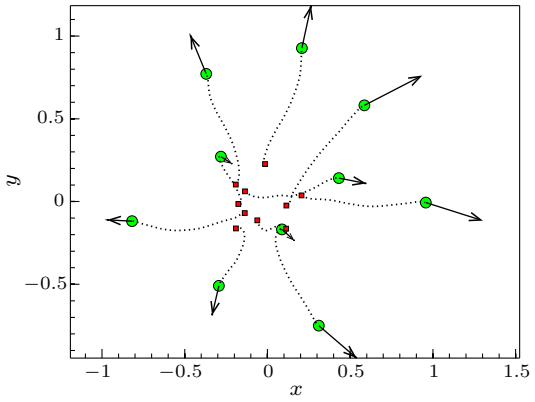

Fig. 2. Snapshot of the system's evolution at $t = 1$ s by using the method proposed in this work. The agents regulate their distance from their neighbors to the desired distance.

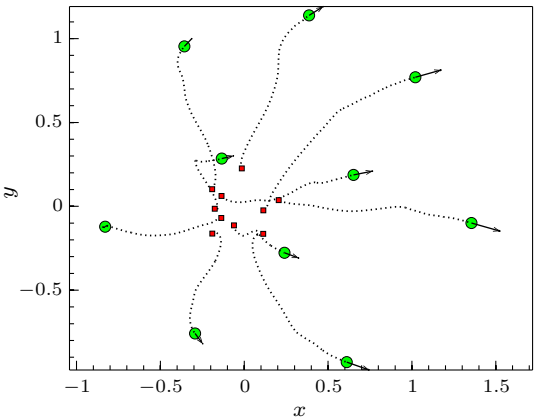

Fig. 3. Snapshot of the system's evolution at $t = 3$ s by using the method proposed in this work. The agents start to match their velocities with their neighbors.

In the simulation example, we will coordinate a system of ten agents into flocking motion with our control scheme. Our agents exist in two dimensions. Initial positions are generated randomly within a square of side length 0.5. Initial velocities are also generated randomly with arbitrary directions and magnitude in the (0,0.5) range.

Let the desired distance $R = 1$ and the maximum detecting range $R_{\max} = 1.5R$. The parameters of the molecular potential field function are chosen to be $A = 100$, $B = 50$. The penalty factors in the fitness function are chosen as $M_1 = 1$, $M_2 = 1$. The maximum magnitude of control input is restricted to 2. The sampling time $\Delta t = 0.01$ s.

Figures 2–4 show the snapshots of the system's evolution at 1 s, 3 s and 10 s, respectively. In these figures, the small circles represent the current position of the agents and the arrows on them represent their current headings. The small squares represent the initial positions of the agents at 0 s and the dotted curves show the trajectory trails of the agents. Note that the axis scales in these figures are different.

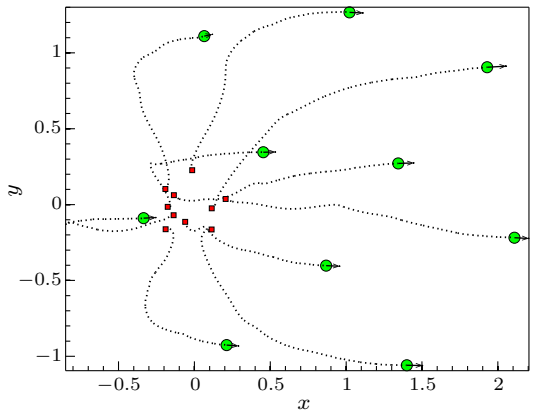

Fig. 4. Snapshot of the system's evolution at $t = 10$ s by using the method proposed in this work. The system converges to a stable formation with the same velocity.

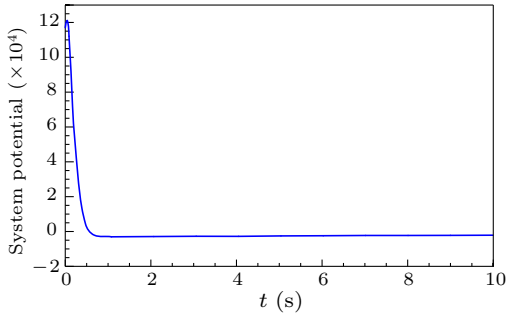

Fig. 5. Time evolution of system potential from $t = 0$ s to $t = 10$ s by using the method proposed in this work.

The figures show that by using our control scheme, the agents regulate their distance to their neighbors to the desired distance in the beginning (Fig. 2). After that, they start to match their velocities with their neighbors (Fig. 3). Finally, the system converges to a stable formation with a common velocity, while agents can avoid collisions at the same time (Fig. 4). It is observed that the trajectory trails of the agents are satisfactory, the convergence is fast and neighboring agents have desired distance eventually, which proves

the strong ability of the molecular potential field and distributed RHC approach to achieve flocking motion. Figure 5 shows the time evolution of the potential of the whole system V_{system} from $t = 0\,\text{s}$ to $t = 10\,\text{s}$. From this figure, it is obvious that the agents regulate the distance between themselves quickly at the beginning, which leads to the fast decrease of the whole system's potential. Then the agents start to match their velocities with their neighbors and group into a stable formation, thus the system potential stays at a very low state.

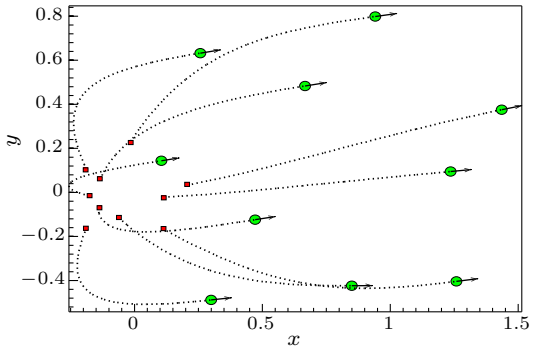

Fig. 6. The system's evolution from $t = 0\,\text{s}$ to $t = 10\,\text{s}$ by using Tanner's control scheme.

We also conduct a comparison between our new control scheme and Tanner's control scheme presented in Ref. [5]. Figure 6 shows the system's evolution from $t = 0\,\text{s}$ to $t = 10\,\text{s}$ by employing Tanner's control scheme. The initial position and velocity of each agent are the same as the previous simulation.

In summary, our proposed molecular potential field and distributed RHC have satisfactory performance for stable flocking of multiple agents, with strong ability to attain the desired stable formation status and collisions can be effectively avoided at the same time. Our future work will focus on investigating how to implement our method by real unmanned vehicles, such as unmanned aerial vehicle (UAV), unmanned ground vehicle (UGV). Furthermore, multiple UAV/UGV heterogeneous cooperation[9] is another challenge for applying the hybrid approach proposed in this work.

References

[1] Reza O S 2006 *IEEE Trans. Automat. Control* **51** p 401
[2] Reynolds C W 1987 *Computer Graphics* **21** p 25
[3] Hettiarachchi S and Spears W M 2009 *Int. J. Intelligent Computing and Cybernetics* **3** p 644
[4] Spears W M, Spears D F, Hamann J C and Heil R 2004 *Autonomous Robots* **17** p 137
[5] Tanner H G, Jadbabaie A and Pappas G J 2003 *IEEE Conference on Decision and Control* (Maui, Hawaii USA) p 2016
[6] Qin Y H 1999 *Heat* (Beijing: Higher Education Press) p 39
[7] Ding B C 2008 *Predictive Control: Theory and Methods* (Beijing: China Machine Press) p 12
[8] Zhang X Y, Duan H B and Yu Y X 2010 *Sci. Chin.* F **53** 223
[9] Duan H B and Liu S Q 2010 *Sci. Chin.* E **53** 1349