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Multi-UAV obstacle avoidance control via multi-objective social learning pigeon-inspired optimization

Key words: Unmanned aerial vehicle (UAV); Obstacle avoidance; Pigeon-inspired optimization; Multi-objective social learning pigeon-inspired optimization (MSLPIO)

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Motivation

- Pigeon-inspired optimization (PIO) is a new swarm intelligence optimization algorithm and has shown great potential. Since it was proposed by Duan and Qiao (2014), it has drawn close attention and has been widely used. The multi-objective optimization problem is one of the important applications of PIO. The UAV flocking problem among obstacles can be regarded as a multi-objective optimization problem.
- The convergence and parameter setting blindness of multi-objective pigeon-inspired optimization (MPIO) is an essential problem.

Main idea

- The social learning mechanism is applied to MPIO. A social learning factor is added to the map compass operator and the landmark operator to improve the convergence.
- Swarm size is an important parameter for PIO and MPIO. It has no specific rules and is usually set at random. Therefore, we adopt a dimension-dependent parameter setting method which determines the swarm size according to the search dimension.

Method

1. Multi-objective social learning pigeon-inspired optimization (MSLPIO)

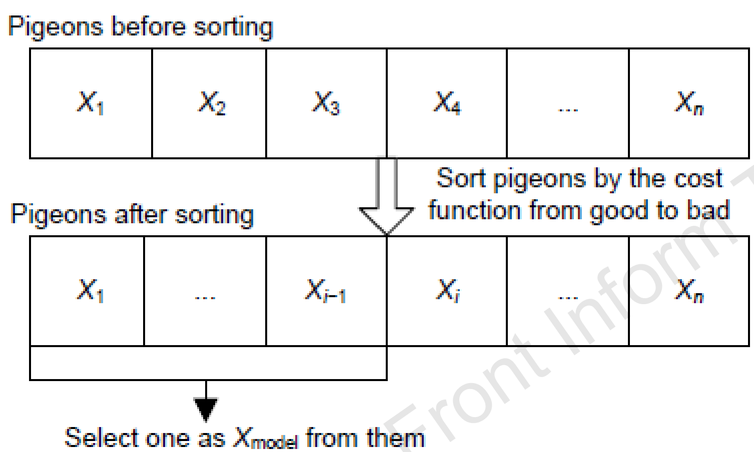

Fig. 1 Social learning mechanism: how to select X_{model}

Algorithm 1 MSLPIO

/* Parameter initialization */

Set M=50, D=5, α=0.5, R=0.3, N_{max}=20, $N_{removed}$=2, N=M+floor(D/5), c1=1−log(D/M), c2=α(D/M), and the upper and lower bounds of the position and velocity

/* Pigeon initialization */

Initialize the positions and velocities of pigeons

Calculate the cost function

Obtain X_{model} and X_{center} by Pareto sorting

/* Main loop */

for nc=1 to N_{max} **do**
    Update positions by Eq. (18)
    Calculate the cost function
    Pareto sorting
    Calculate X_{center} by Eq. (15)
    Store the Pareto frontier in A
    Pick one solution from A as X_{model}
    nc=nc+1
    N=N−$N_{removed}$
end for
Output the Pareto frontier

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2. Multi-UAV obstacle avoidance control strategy via MSLPIO

Algorithm 2 The proposed control strategy

Parameter initialization
for t=1 to $T_{\max}$ **do**
  for i=1 to N **do**
    Calculate control components by Eqs. (5)–(10)
    Obtain weight factor α by MSLPIO
    Obtain the final control variables and the control input of the i^{th} UAV by Eqs. (2)–(4)
    Obtain the i^{th} UAV state by Eq. (1)
    i=i+1
  end for
t=t+1
end for
Output all UAV states

Major results

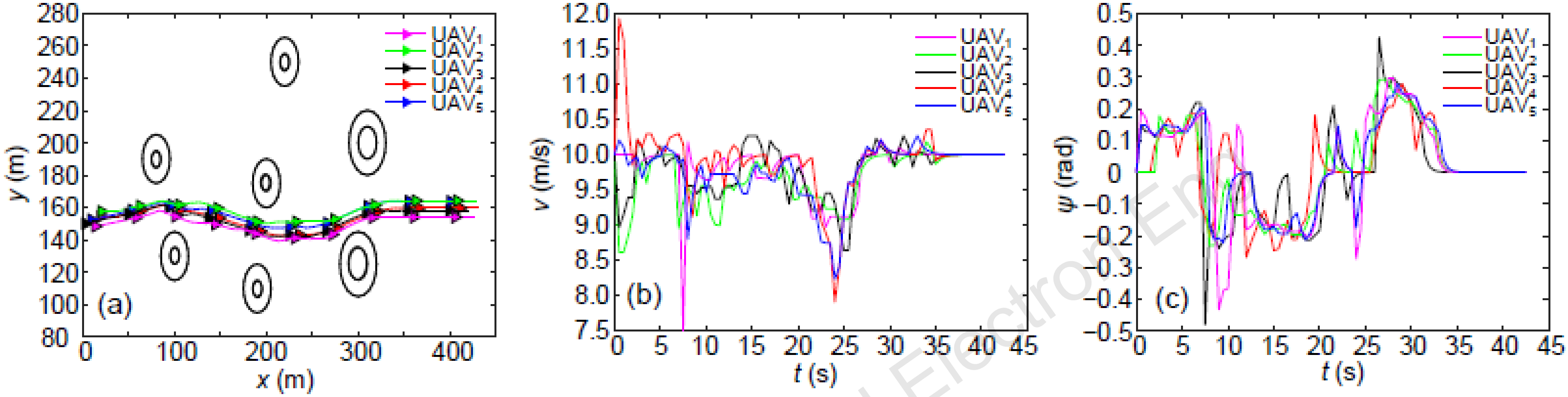

Fig. 2 Simulation results of MSLPIO: (a) obstacle avoidance process of UAV flocking; (b) velocity curves of UAVs; (c) yaw angle curves of UAVs

Circles represent the obstacles, triangles represent the UAVs, and curves represent the flight paths of multiple UAVs

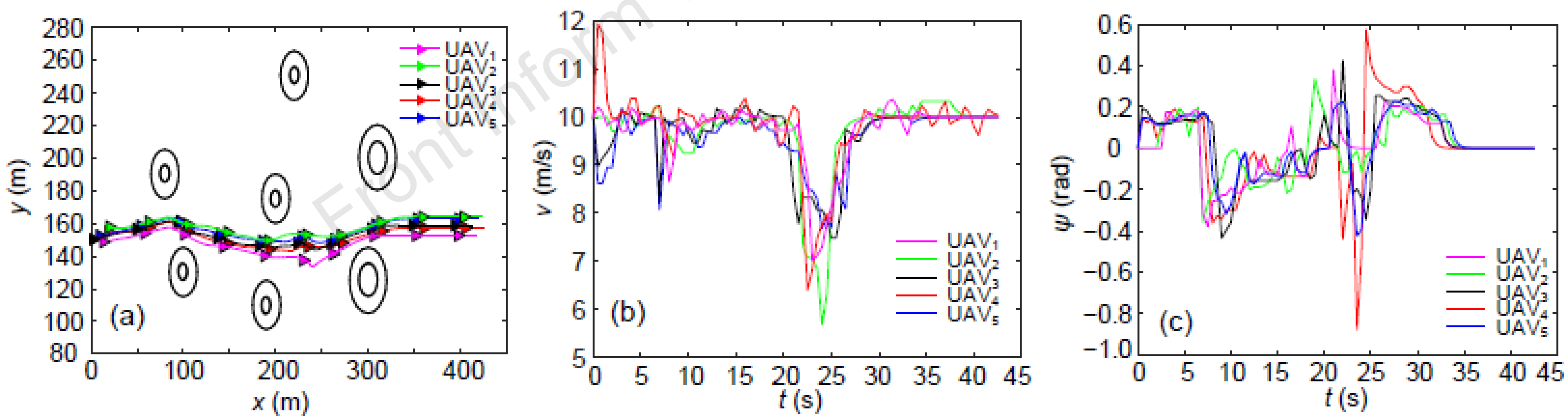

Fig. 3 Simulation results of MPIO: (a) obstacle avoidance process of UAV flocking; (b) velocity curves of UAVs; (c) yaw angle curves of UAVs

Circles represent the obstacles, triangles represent the UAVs, and curves represent the flight paths of multiple UAVs

Major results (Cont’d)

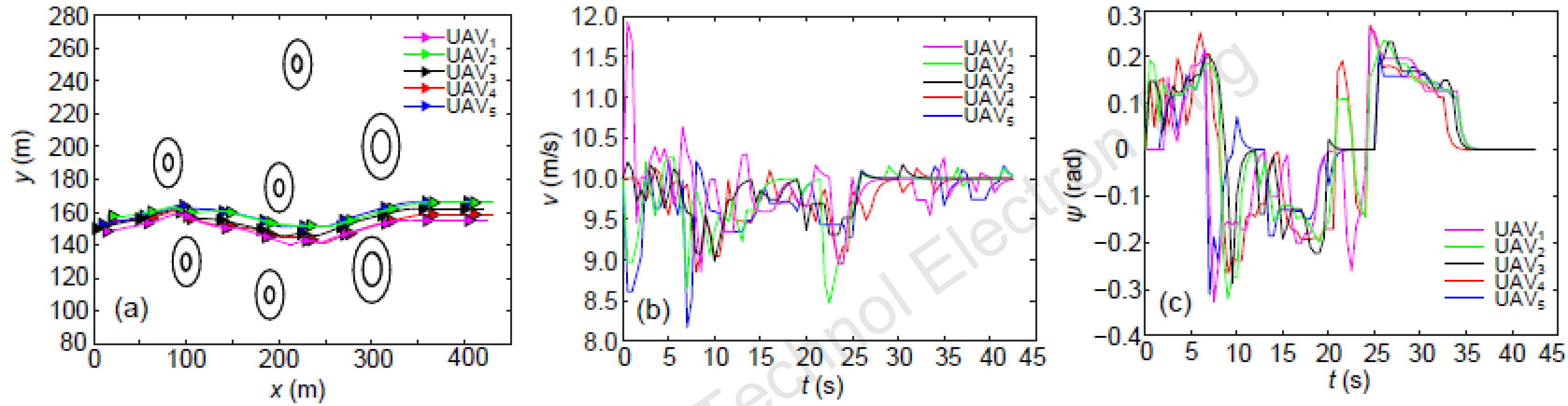

Fig. 4 Simulation results of NSGA-II: (a) obstacle avoidance process of UAV flocking; (b) velocity curves of UAVs; (c) yaw angle curves of UAVs

Circles represent the obstacles, triangles represent the UAVs, and curves represent the flight paths of multiple UAVs

Table 1 Statistical results of the three algorithms

Algorithm	Convergence time of velocities	Convergence time of yaw angles (s)
MSLPIO	37 s	33.75
MPIO	$>T_{\max}$	35.15
NSGA-II	$>T_{\max}$	36.22

$T_{\max}$: maximum running time

Conclusions

In this study, we have improved MPIO using a social learning mechanism and successfully applied it to multi-UAV obstacle avoidance. The main conclusions are as follows:

(1) The flocking control strategy does not need prior information about the environment, and the control framework is highly portable.

(2) The convergence and consistency of MSLPIO are better than those of the state-of-the-art algorithms, and UAV flocking can quickly converge to the expected level after crossing the obstacle areas.