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Original research article

Monitoring trajectory optimization for unmanned surface vessel in sailboat race

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ABSTRACT

This paper aims to optimize the monitoring trajectory of unmanned surface vessel (USV) attached with optical camera in applications such as sailboat race. It can be taken as the waypoints optimization problem with the index of minimal energy consumption and obstacle avoidance under water current. Grey wolf optimizer (GWO), which is a novel intelligent method imitating the leadership hierarchy and hunting mechanism of wolf swarm, is utilized to obtain the optimal trajectory. Considering the unsatisfactory searching ability of GWO in complex scenarios, the improved grey wolf optimizer (IGWO) is then proposed by introducing the grey wolf individual memory, the nonlinear convergence factor, and the selected initial population obtained from the tangent method. Finally the simulation results demonstrate the robustness, efficiency and feasibility of IGWO in different cases.

1. Introduction

With the advantages of flexibility and cost-effectiveness, unmanned surface vessel (USV) is increasingly utilized in military or civilian fields such as sea patrol, oceanography, water environment surveillance, communication relay and so on [\[1,](#page--1-0)[2](#page--1-1)]. This paper takes the sailboat race monitoring as an application example, where a USV attached with optical camera sensor is utilized to collect race information for live TV broadcast or analysis. Suppose that the sequential monitoring points are already determined, and this paper aims to optimize the energy-minimum and obstacle-avoiding trajectory between two monitoring points.

The monitoring trajectory optimization problem for USV is actually similar to the traditional path planning problem [[3](#page--1-2)[,4\]](#page--1-3), and researchers have proposed various methods. Based on the modelling type of configuration space, these methods can be classified into the grid map-based methods (such as A*, Theta*, Fast Marching, Dijkstra) [\[5–7](#page--1-4)], the sampling-based methods such as probabilistic roadmap or rapidly-exploring random tree (RRT) [\[8,](#page--1-5)[9\]](#page--1-6), the potential field methods such as artificial potential field (APF) or interfered fluid dynamical system (IFDS) $[10-12]$, the optimization-based methods (such as mixed integer linear programming, intelligent methods) [\[13–15](#page--1-8)]. Kim et al. [\[5](#page--1-4)] constructed a non-uniform grid map reflecting the geometric cost and then extended the dimension with the kinematic constraint of USV. In Ref. [\[12](#page--1-9)], the interfered fluid dynamical system was proposed to plan the obstacle-avoiding path with the good path quality and little calculation amount. It should be noticed that, however, most methods have their weaknesses and advantages respectively. For example, A* has been used on the real platform successfully because of its simple principle, but unfortunately the calculation amount will enlarge explosively if the dimension of configuration space increases. RRT method can easily avoid the local optimal problem which exists widely in other methods, but the path quality is unsatisfactory due to its

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mechanism of random sampling.

Intelligent methods have the operating mechanisms imitating various nature phenomena, so they are the promising ways to solve the trajectory optimization problem, which can be taken as a complicated NP-hard problem with the sophisticated indexes such as energy consumption, danger level for obstacle avoidance, etc. Compared to those deterministic algorithms, the intelligent methods have some stochastic operators for global searching and local searching simultaneously, and some intrinsic superiorities such as flexible independency and simple principle [[16\]](#page--1-10). Researchers have introduced some mechanisms into traditional intelligent methods such as particle swarm optimization (PSO) and genetic algorithm (GA), or even utilized some new intelligent algorithms such as ant lion optimizer (ALO) and memetic algorithm [[17–19\]](#page--1-11). For example, Ref. [[17\]](#page--1-11) proposed the multi-frequency vibrational genetic algorithm (mVGA), whose initial population is generated by the clustering method and Voronoi diagram. Yao et al. [\[19](#page--1-12)] presented the dynamic adaptive ALO by introducing the operators of Levy flight and 1/5 principle-based adjustment strategy, and solved the route planning problem well in different cases.

Grey wolf optimizer (GWO) is a new intelligent population-based algorithm by imitating the social hierarchy and predatory strategy of grey wolfs [\[20](#page--1-13)]. Compared to other standard methods, this method is of higher convergence speed and stronger stability, and has been developed in many fields [[21–24\]](#page--1-14). Saremi et al. [\[22](#page--1-15)] utilized the evolutionary population dynamics in order to remove the poor searching agents and reinitialize the worst searching agents around the abstract space. It could significantly improve the performance of exploration, exploitation, robustness and convergence speed. Ref [\[23](#page--1-16)] adopted GWO as the solver of model predictive control (MPC) formulation for target tracking problem. Instinctively GWO method is adopted in this paper to solve the trajectory optimization problem. However, the performance of basic GWO may be unsatisfactory when utilized in the complex cases, such as the scenario with dense obstacles where the safe obstacle-avoiding trajectory cannot be obtained sometimes. Hence the improved GWO (IGWO) is proposed here by introducing the grey wolf individual memory inspired by PSO, the nonlinear convergence factor, and the selected initial population obtained from the tangent method. To verify the effectiveness of IGWO, it is compared with PSO and GWO in different cases. It is concluded that IGWO generates the optimal trajectory with higher quality and better stability.

The remaining paper is organized as follows. Section [2](#page-1-0) models the trajectory optimization problem, including the trajectory representation and objective functions. Section [3](#page--1-17) describes the IGWO method and its application to trajectory optimization problem. The simulation results are given in Section [4.](#page--1-18) In the last section the conclusion is drawn.

2. Problem description

This paper takes the sailboat race monitoring as an example, where the sequential monitoring points (denoted as *MP*) needed to be visited by USV attached with optical camera are already determined in advance. Hence the aim of this paper is to optimize the USV trajectory between any two monitoring points MP_i and MP_{i+1} , along which USV would avoid obstacles (e.g., sailboats, other ships, tropical cyclones, etc.) safely and reach the destination (i.e. MP_{i+1}) from the start point (i.e. MP_i) with the minimum energy consumption. Obviously it is similar to the traditional path planning problem for ground robot, unmanned aerial vehicle, autonomous underwater vehicle, etc.

2.1. Modeling of trajectory

This paper utilizes a simplified model with the constant *x*-coordinate increment to represent the trajectory. As shown in [Fig.1,](#page-1-1) the straight line connecting MP_i and MP_{i+1} is equally divided into $D + 1$ parts, and the perpendicular lines denoted by $\{L_1, \dots, L_d, \dots, L_D\}$ at all the segment points are determined. Then only one point will be chosen from each line, and all of them compose the waypoint set ${[MP_i, P_1, \dots, P_d, \dots, P_D, MP_{i+1}]}$. By connecting these waypoints successively, the trajectory can be obtained. Besides, the coordinate system o-*xy* can be transformed into $o' - x'y'$ where the point MP_i is taken as the origin while the line MP_iMP_{i+1} is the *x* axis. Hence the waypoint set is redefined as $\{MP'_i, P'_1, \dots P'_d, \dots, P'_D, MP'_{i+1}\}$ where $MP'_i = (0, 0), P'_d = (x'_d, y'_d)$ and $MP'_{i+1} = (\{MP_iMP_{i+1}\}, 0)$. It is obvious that the *x*-coordinates of waypoints are fixed with the constant increment $|MP_1MP_{i+1}|/(D + 1)$, so only the *y*-coordinates ${y'_1, \dots, y'_d, \dots, y'_D}$ need to be optimized.

Fig. 1. The model of USV trajectory.

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