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Cooperative Path Planning for Heterogeneous Unmanned Vehicles in a Search-and-Track Mission Aiming at an Underwater Target

Yu Wu*, K. H. Low, Chen Lv

Abstract—It is an effective way to execute a complicated mission by cooperating unmanned vehicles. This paper focuses on a search-and-track (SAT) mission for an underwater target, and the mission is implemented by combining an unmanned aerial vehicle (UAV), an unmanned surface vehicle (USV) and an autonomous underwater vehicle (AUV). In the cooperative path planning model, the mission is divided into the search phase and the track phase, and the goals of the two phases are to maximize the search space and minimize the terminal error respectively. The constraints contain the maneuverability of vehicles and communication ranges between vehicles. Strategies based on random simulation experiments and asynchronous planning are developed to design the cooperative path planning algorithm in the two phases, and the paths are generated by an improved particle swarm optimization (IPSO) algorithm in a centralized or a distributed mode. Simulation results demonstrate that the proposed method can deal with different situations. The UAV&USV&AUV system is superior to the USV&AUV system in the SAT mission.

Index Terms—unmanned aerial vehicle, unmanned surface vehicle, autonomous underwater vehicle, cooperative path planning, asynchronous planning

It has become popular for cooperation among unmanned vehicles to perform various tasks because compared to a single vehicle, the success rate of the mission can be increased. Cooperation can be realized by homogeneous vehicles and heterogeneous vehicles. For homogeneous vehicles, unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs), unmanned surface vehicles (USVs) or autonomous underwater vehicles (AUVs) are usually deployed to execute tasks in the air, on the ground, on the water surface and underwater respectively. In complicated tasks, heterogeneous vehicles, such as UAV&UGV system, UAV&USV system, UAV&AUV system, are used. In those systems, heterogeneous vehicles play different roles according to their characteristics and the demand.

In this paper, a new UAV&USV&AUV system is introduced to finish the search-and-track mission (SAT) aiming at an underwater target, and the cooperation mechanism among heterogeneous vehicles is studied.

For the cooperation among homogeneous vehicles, UAVs can save communication energy [1], detect geomorphic change [2] and so on. A novel k -degree smoothing-based coordinated path planning method for multi-UAVs is proposed in Ref. [3]. UGVs can go for road detection and extract features from a large dataset of multiple images. In Ref. [4], taxi paths from different starting positions to destinations are generated, and both the efficiency and safety are enhanced by the proposed planning architecture and strategy. A team of USVs are usually appointed to carry out search and rescue tasks. A new intelligent multi-task allocation and path planning algorithm is proposed in Ref. [5] based on the self-organizing map and the fast-marching method. As for AUVs, data collection, maintenance of submerged oil wells and deployment of benthic stations are a few applications of them. The cooperative hunting problem of heterogeneous AUVs is studied in Ref. [6], and a novel spinal neural system-based approach is proposed.

Compare to the studies on cooperation among homogeneous vehicles, the reports on heterogeneous vehicles are relatively rare. In many cases, UAVs are mixed with other types of vehicles. In a UAV&UGV system, UAV is used to obtain the ground image from aerial vision, which is then transmitted to UGV to construct the ground map and improve the recognition accuracy of obstacles [7]. Similar to the UAV&UGV system, USV also can be regarded as the platform for UAV taking off and landing [8]. The problem of monitoring ocean pollution and cleaning dirty zones is solved by a UAV&USV system in Ref. [9]. UAV monitors multiple ocean regions and USV tackles the cleaning of dirty zones. Genetic algorithm is applied to plan paths from the starting to the destination. The study on UAV&AUV system is limited as AUV is sometimes forbidden to communicate with UAV when the AUV is underwater for safety reason. They can exchange information only when the AUV has risen to the water surface. In Ref. [10], three strategies, i.e., periodic coordination, shortest route coordination and probabilistic coordination are proposed to determine the communication mechanism between UAV and AUV, and the goal is to maximize the explored area while minimizing the idle time of UAV and AUV. A USV&AUV system also can complete the above task. In this mode, acoustic communication and positioning system is used to establish the surface underwater communication network and improve the

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navigation and control performance [11].

To conclude the existing works mentioned above, the SAT mission aiming at an underwater target can be addressed by a single AUV, AUVs, UAV&AUV system or USV&AUV system. However, there are still some drawbacks. USV and AUV have a relatively weak ability in search [12], and the communication between UAV and AUV is inefficient [13]. In this paper, a novel UAV&USV&AUV system is deployed to deal with the above problems and further enhance the efficiency of mission completion. So far, such a heterogeneous system is rarely reported. The main contributions of this work can be concluded as follows:

(a) The framework of heterogeneous system is developed, in which the communication mechanism and information flow among vehicles are defined. Various possibilities during the mission are considered and the corresponding countermeasures are proposed.

(b) The model for SAT mission is established. The motion of vehicle is described by kinetic equations of particle, and the maneuverability of vehicle is taken into account. Kalman filtering integrating the motion model of target is designed to predict its future position. The constraints on communication mechanism and detection distance are included. Besides, the maximum search space and the minimum track error of AUV are treated as optimization indexes in the search and track phase respectively.

(c) Cooperative strategy and path planning algorithm for the heterogeneous system is developed. In the search phase, a centralized approach with random simulation experiments is proposed to reduce the complexity of calculating the search space combined by UAV, USV and AUV. In the track phase, a distributed mode with asynchronous planning strategy [4] is proposed to allocate various constraints to small branches, which can then be covered separately by different vehicles.

I. DESCRIPTION OF THE SAT MISSION AND THE HETEROGENEOUS SYSTEM

The SAT mission is described as follows: a UAV, a USV and an AUV work cooperatively to search the underwater target. When the target is detected by one of the vehicles, the search phase is completed. Then the information of target position will be ultimately sent to AUV, and the AUV is responsible for tracking the target. The mission won't be stopped until the distance between the AUV and target is smaller than a threshold. In the above process, USV is the relay because the direct communication between UAV and AUV is forbidden. The scenario of mission is shown in Fig. 1.

Fig. 1. Composition of the heterogeneous system searching and tracking

an underwater target

In the search phase, the three vehicles work in a centralized way, and the target may be found first by AUV, USV or UAV. The three cases are defined as Case 1, Case 2 and Case 3 respectively for convenience. Case 1 is the simplest. UAV and USV are not involved in the track phase, and AUV should shorten the distance from the target before the end of mission. In Case 2, after USV has detected the target, it will keep the target within the maximum detection distance and send the position information to AUV. As for Case 3, which is the most complicated case, UAV will be able to first identify the detection range of a target before sending the target's latest position to USV. According to the work mode of vehicles in the track phase, UAV, USV and AUV can determine their paths in a distributed way.

II. MATHEMATICAL MODEL OF THE HETEROGENEOUS SYSTEM

A. Motion models for vehicles and underwater target

All vehicles are simplified as particles navigating in three-dimensional space. In the ground frame, the sea surface level is defined as the plane OXY , and the axis Z is vertically upward according to the right-hand rule. The kinetic model for vehicles is presented as follows [14]:

$$\begin{cases} \dot{x} = V \cos \theta \cos \varphi \\ \dot{y} = V \cos \theta \sin \varphi \\ \dot{z} = V \sin \theta \\ \dot{\theta} = q \\ \dot{\varphi} = r \\ \dot{V} = a \end{cases} \quad (1)$$

where (x, y, z) and V denote the position and velocity of the vehicle, respectively. Note that θ and φ are pitch angle and yaw angle, and q and r are the angular rates correspondingly, while a is the acceleration. Note that a subscript A, S, U or T are added to the above variables to denote the states of UAV, USV, AUV or the target respectively. In Eq. (1), the control variable of vehicle is defined as $\mathbf{u} = [q \ r \ a]^T$, and the state variable is $\mathbf{x} = [x \ y \ z \ V \ \theta \ \varphi]^T$.

Maneuverability of vehicle is introduced to reflect the ability of changing velocity, height and motion direction. The constraints on control variables must be limited within a certain range to denote the capability. In this study, UAV flies at an unchanged height, and USV sails on the water surface. The constraints on q, r and a are listed below:

$$\begin{cases} q_A = 0 \\ |r_A| \leq r_{Amax} \\ |a_A| \leq a_{Amax} \end{cases} \quad (2)$$

$$\begin{cases} q_S = 0 \\ |r_S| \leq r_{Smax} \\ |a_S| \leq a_{Smax} \end{cases} \quad (3)$$

$$\begin{cases} |q_U| \leq q_{Umax} \\ |r_U| \leq r_{Umax} \\ |a_U| \leq a_{Umax} \end{cases} \quad (4)$$

$$\begin{cases} |q_T| \leq q_{Tmax} \\ |r_T| \leq r_{Tmax} \\ |a_T| \leq a_{Tmax} \end{cases} \quad (5)$$

In this study, the motion law of target is unknown, and only its current position can be obtained by measurement. To give a

general situation, the target is assumed to move randomly. Therefore, q_T , r_T and a_T are random numbers satisfying the constraints in Eq. (5).

The current position of target can be detected by vehicles if it is within the maximum detection distance, and its position in the next sample time only can be predicted based on the collected data. Here a Kalman filtering-based method is used.

The linear differential equations of Kalman filtering denoting the motion of target are given by

$$\begin{cases} X(k) = AX(k-1) \\ Z(k) = HX(k) \end{cases} \quad (6)$$

where X is the state of target, Z is the observed value, A is the transfer matrix from sample time $k-1$ to k , and H is the transfer matrix from. Here A and H are determined by combining the motion equations of target, as listed below:

$$\begin{cases} s(k) = s(k-1) + v(k-1)T + \frac{1}{2}a(k-1)T^2 \\ v(k) = v(k-1) + a(k-1)T \\ s_z(k) = s(k) + v(k) \end{cases} \quad (7)$$

where T is the time interval between two adjacent sample time, s_z is the observed value, and s and v are the actual position and velocity. In Eq. (7), the motion of target is approximated to be uniformly accelerated during T . The matrix form of Eq. (7) is denoted by the following equations:

$$X(k) = \begin{bmatrix} x(k) \\ x'(k) \\ y(k) \\ y'(k) \\ z(k) \\ z'(k) \end{bmatrix} = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k-1) \\ x'(k-1) \\ y(k-1) \\ y'(k-1) \\ z(k-1) \\ z'(k-1) \end{bmatrix} + \begin{bmatrix} \frac{T^2}{2} & 0 & 0 \\ 0 & T & 0 \\ 0 & 0 & \frac{T^2}{2} \\ 0 & T & 0 \\ 0 & 0 & \frac{T^2}{2} \\ 0 & 0 & T \end{bmatrix} \begin{bmatrix} a_x(k-1) \\ a_y(k-1) \\ a_z(k-1) \end{bmatrix} \quad (8)$$

$$Z(k) = \begin{bmatrix} x_z(k) \\ y_z(k) \\ z_z(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x(k) \\ x'(k) \\ y(k) \\ y'(k) \\ z(k) \\ z'(k) \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} v_x(k) \\ v_y(k) \\ v_z(k) \end{bmatrix} \quad (9)$$

From Eq. (8) and (9), A and H can be denoted as

$$A = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (10)$$

Note that there are two forms of equations describing the motion of target. Eq. (1) shows the real motion. Eq. (7) is used to predict the movement of target, and the formulas of using Kalman filtering can be found in Ref. [15].

B. Constraints on the states of vehicles

In this SAT mission, the states of vehicles must obey specific constraints to ensure the safety and effective communications. Those constraints are discussed next.

1. Constraint on feasible space

The vehicles must move within a certain space, which is governed by

$$\begin{cases} x_{min} \leq x_A, x_S, x_U, x_T \leq x_{max} \\ y_{min} \leq y_A, y_S, y_U, y_T \leq y_{max} \\ z_{min} \leq z_U, z_T < 0 \\ z_A = const \\ z_S = 0 \end{cases} \quad (11)$$

where x_{min} , x_{max} , y_{min} and y_{max} are the boundaries of plane OXY , and z_{min} is the greatest depth that the AUV can dive.

2. Constraint on velocities of vehicles

The vehicles must navigate within their performance. Here the maximum velocity is defined for each vehicle as

$$\begin{cases} |V_A| \leq V_{Amax} \\ |V_S| \leq V_{Smax} \\ |V_U| \leq V_{Umax} \\ |V_T| \leq V_{Tmax} \end{cases} \quad (12)$$

3. Terminal constraint

The AUV should be close to the target as much as possible in the ending moment. The terminal distance between the AUV and the target must be smaller than the threshold to terminate the SAT mission, as given by

$$||P_U(t_f) - P_{tar}(t_f)|| \leq dis_{U-T} \quad (13)$$

where P_U and P_{tar} are respectively the position of AUV and underwater target, while t_f is the ending moment. Note that the operator $|| \cdot ||$ in Eq. (13) is used to calculate the distance between two points, while dis_{U-T} is the threshold.

4. Maximum detection range and communication range between vehicles

In this study, the detection range of the vehicles is assumed to be spheres, and the maximum radius of sphere is defined as d_{det} . Besides, to realize normal communication between vehicles, the distance between UAV and USV and between USV and AUV need to be smaller than d_{A-S} and d_{S-U} , respectively.

C. Optimization indexes in search and track phase

In the search phase, the search space of vehicles should be as large as possible to increase the probability of detecting the target. In the track phase, the distance between AUV and the target should be as small as possible to reduce the terminal error. The goal of each phase can be expressed as follows:

$$J_1 = \max ((V_{UAV} \cup V_{USV} \cup V_{AUV}) \cap V_{z \leq 0}) \quad (14)$$

$$J_2 = \min (||P_U(t_f) - P_{tar}(t_f)||) \quad (15)$$

where V_{UAV} , V_{USV} , V_{AUV} are the search space of UAV, USV and AUV, and $V_{z \leq 0}$ is the space below the water surface.

III. PATH PLANNING ALGORITHM FOR COOPERATIVE SEARCH-AND-TRACK (SAT) MISSION

As the search and track phases are relatively independent in this mission, the two sub-problems can be dealt with separately. Receding horizon optimization is adopted to online planning.

An improved particle swarm optimization (IPSO) algorithm is proposed to obtain the paths of vehicles in a centralized or distributed way in the two phases.

A. Cooperative search algorithm using random simulation experiments

The best way to increase the probability of detecting target is to maximize the search space. An estimation strategy based on random simulation experiments is developed. The length, width and height of the underwater space can be evenly divided into N_a , N_b , and N_c parts respectively [16], and the values of N_a , N_b , and N_c can be adjusted to meet the demand of online computation.

For a specific position combination of UAV, USV and AUV, the volume of search space can be measured by the number of points falling into the combinational space. The optimization index in Eq. (14) is updated as follows:

$$J_1 = \min ((N_a + 1)(N_b + 1)(N_c + 1) - N_{space}) \quad (16)$$

where N_{space} is the number of points within the search space composed by UAV, USV and AUV.

B. Asynchronous planning strategy in the track phase

As the paths of vehicles are determined in a distributed mode, an asynchronous planning strategy is developed to make them work with a certain order in each sample time.

At each sample time k , the vehicle having detected the target broadcasts the current position of it. The AUV will then plan the path first because the track mission is actually implemented by it. There should be fewer constraints imposed on the path of AUV to result in a better result, so the constraint on communication range between USV and AUV is not included. AUV determines its path considering the predicted position of target and the optimization index in Eq. (15). Based on the action of AUV, USV plans its path next (in Cases 2 and 3). Compare to the path planning of AUV, the constraint on the distance between USV and AUV is added when the communication is needed. The optimization index for the action of USV is expressed as

$$J_{2USV} = \min (d_{S-T}(k+1)) \quad (17)$$

where $d_{S-T}(k+1)$ is the distance between USV and the target in the sample time $(k+1)$. UAV is the last one to generate its path in each sample time, and it is fit for Case 3. Similar to USV, the constraint on the distance between UAV and USV is considered. The optimization index for UAV's decision is also the distance from the target in the next sample time.

$$J_{2UAV} = \min (d_{A-T}(k+1)) \quad (18)$$

C. Improvement of PSO algorithm for cooperative path planning

Meta-heuristic algorithms have been widely applied in path planning problems and have demonstrated their advantages. PSO algorithm is one of the most popular meta-heuristic algorithms. There are numerous examples that PSO algorithm is used in online optimization problems [17, 18]. In the search phase, the system is organized in a centralized mode, and the control variables are $\mathbf{u}^1 = [r_A \ a_A \ r_S \ a_S \ q_U \ r_U \ a_U]^T$. The control variables in the track phase are $\mathbf{u}_{UAV}^2 = [r_A \ a_A]$,

$\mathbf{u}_{USV}^2 = [r_S \ a_S]$ and $\mathbf{u}_{AUV}^2 = [q_U \ r_U \ a_U]$ for different vehicles. The control variables are updated according to the formulas of PSO algorithm. Note that if any element of control variable violates the constraints in Eq. (2), (3) or (4), it will be set to the closest threshold to keep the algorithm running.

To further improve the performance of PSO algorithm, some modifications are developed. First, the initial values of control variables obey normal distribution to traverse the permitted range. ω , c_1 and c_2 are set to decrease linearly according to Ref. [19]. At last, an implicated time factor is introduced to the position update formula as given by

$$\mathbf{u}_i(t+1) = \mathbf{u}_i(t) + \Delta \mathbf{u}_i(t)TF \quad (19)$$

where TF is the time factor.

In summary, the three modifications mentioned above can make the global and local search ability of PSO algorithm adapt to the current iteration times without increasing the computational cost. As there are only a few control variables, a small number of initial solutions and a fewer iteration times can result in a solution good enough, which also reduces the elapsed time of path planning. Note that, the quality of solution is evaluated by Eqs. (15)- (18). If any constraint in Section II.B is violated, the fitness value will be defined as a large number to abandon it.

IV. SIMULATION STUDIES

To investigate the superiority of the proposed cooperative path planning method for underwater target SAT mission, simulations under different situations are conducted. In the first group, three different initial positions of underwater target are considered, and the proposed algorithm can deal with different cases. In the second scenario, the benefits of the UAV&USV&AUV system are demonstrated by comparing with a USV&AUV system. All the results are obtained by running the programs on MATLAB 2016a with a desktop (equipped with Intel Core i7-3370 3.40 GHz). In IPSO algorithm, the scale of swarm is set to 10, and the maximum iteration time is 20. Important constraints are set as $d_{det}=1000\text{m}$, $d_{A-S}=3000\text{m}$, $d_{S-U}=500\text{m}$ and $dis_{U-T}=2\text{m}$, respectively.

A. Results of the SAT mission in different cases

Three different initial positions of target are considered to explore their influences on the results. The 3D paths of vehicles in each case are presented in Fig. 2.

Fig. 2. 3D paths of vehicles in different cases

In all of the three cases, the AUV can track the target successfully. To demonstrate that the obtained results can satisfy the proposed constraints, the distance between the vehicles and the target and the distance between different vehicles are shown in Figs. 3 and 4, respectively.

Fig. 3. Distance between the vehicles and target in three cases

Fig. 4. Distance between different vehicles in three cases

The vertical black dotted lines are the junctions of the two phases. In Cases 1, 2 and 3, it is the AUV, USV and UAV that discovers the target first, and the three cases cover all the possibilities in the search phase. The distance between different vehicles are all within the permitted ranges, which guarantees the normal communication between vehicles.

Next, some important data in the above results are listed to provide more information, as shown in TABLE I.

TABLE I IMPORTANT DATA IN THE SAT MISSION

	Case 1	Case 2	Case 3
Detected moment of target	AUV: 22s	USV: 13s; AUV: 43s	UAV: 7s; USV: 33s; AUV: 76s
Ending moment of mission	184s	200s	298s
$dis_{U-T}(t_f)$	0.83m	0.69m	0.45m

In all the three cases, the target can be tracked within the threshold. It costs the least time to complete the mission in Case 1 because it is the simplest. AUV detects the target first and then tracks it directly. There is no information exchange among vehicles in the track phase, which saves much time. In Case 2, USV discovers the target first and sends the position to AUV. At 43s, AUV detects the target and begins to track it. For a more

common case, UAV will first find the target with less time compared to Cases 1 and 2 for its high flight velocity, which enables it to cover more space within the same time interval. However, in this case, extra time is added before AUV has detected the target, which increases the ending time of whole mission.

B. Comparison between different systems: UAV&USV&AUV vs. USV&AUV

A USV&AUV system is introduced to accomplish the same mission. The initial conditions are the same with those in Case 3. The 3D paths of vehicles and targets are shown in Fig. 5.

Fig. 5. Result of the USV&AUV system

Results in Figure 5 show that AUV is able to track the underwater target. Results for the distance between vehicles are given in Fig. 6.

Fig. 6. Distance of USV-target, AUV-target and USV-AUV

As depicted in Fig. 7, the distance between USV and AUV is smaller than 500m, and the normal communication is ensured. The target is detected firstly by USV at 26s, and it is found by AUV at 132s. AUV completes the track mission at 321s, and the terminal error is 1.97m. Compared to the results in TABLE I, the search ability of USV&AUV system is weaker. With the guidance of UAV, AUV can detect the target earlier. In other words, the UAV&USV&AUV system is superior to USV&AUV system in accomplishing the SAT mission.

V. CONCLUDING REMARKS

The cooperative path planning problem in an SAT mission aiming at an underwater target is studied in this paper, and the mission is completed by deploying a UAV&USV&AUV system. Literature investigation shows that current unmanned systems suffer from drawbacks in this mission, and the cooperation among UAV, USV and AUV has advantages in search and communication.

Firstly, the architecture of UAV&USV&AUV is introduced. In the mathematical model, the motion of vehicles is described by kinetic equations, and the position of target is predicted based on Kalman filter. The whole mission is divided into two

phases, and the constraints are organized under this framework. The optimization indexes in the two phases are to maximize the search space and minimize the terminal track error respectively.

To solve the established cooperative path planning model, receding horizon optimization is adopted, and a centralized mode and a distributed mode are developed to generate the path in the two phases respectively. In the search phase, a strategy based on random simulation experiments is conducted to simplify the online calculation, and an asynchronous planning strategy is adopted to reduce conflicts during path planning.

In simulation studies, different cases are considered, and the proposed method is able to cover various situations successfully. It is also found that the UAV&USV&AUV system is more efficient than the USV&AUV system in accomplishing the SAT mission. In the future, more complicated task can be considered for this UAV&USV&AUV system, and the concept of 'AirMatrix' for the traffic management of unmanned aircraft systems [20] can be introduced to incorporate into the model developed in the present work. Experiments embedded hardware and software can be explored to demonstrate the validity and the performance of the method developed.

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