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USV TRAJECTORY PLANNING FOR TIME VARYING MOTION GOALS IN AN ENVIRONMENT WITH OBSTACLES

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ABSTRACT

Safe and efficient following of a time varying motion goal by an autonomous unmanned surface vehicle (USV) in a sea environment with obstacles is a challenge. The vehicle's tracking capability is inherently influenced by its dynamics, the motion characteristics of the motion goal, as well as by the configuration of obstacles in the marine environment. We have developed an approach that utilizes a lattice-based trajectory planning to generate a dynamically feasible, resolution optimal, collision-free trajectory to allow the vehicle to reliably reach the motion goal. We utilized a trajectory following controller to achieve high tracking efficiency while still preserving motion safety. The entire approach is based on the developed USV system architecture that encapsulates the necessary trajectory planning components. We demonstrated the effectiveness of the developed planner in a simulated environment with static obstacles. In addition, we have developed a physical evaluation setup.

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INTRODUCTION

Autonomous unmanned surface vehicles (USVs) [1] have been emerging as an attractive alternative to human-driven boats in a wide variety of missions that require reliable sea navigation. Examples of such missions include harbor patrolling and protecting important assets in vulnerable areas [2, 3], surveillance [4], environmental monitoring [5], etc. These applications usually require the vehicles to carefully navigate through locations with many obstacles with variable dimensions and shapes such as boats, shorelines, or docks.

Many of the applications require frequent computation of a motion goal by the USV to successfully fulfill its task. The motion goal may be rapidly changing and express different motion patterns depending on the task. Examples of the tasks include interception, follow target boats, rules of the road (COLREGS) [6], intruder blocking [7], etc. In this paper, our focus is on the development of a trajectory planning approach for safe and efficient following of a moving target in a marine environment with obstacles (see Figure 1). Safe and efficient target following requires the autonomous USV to keep the target within a user-specified

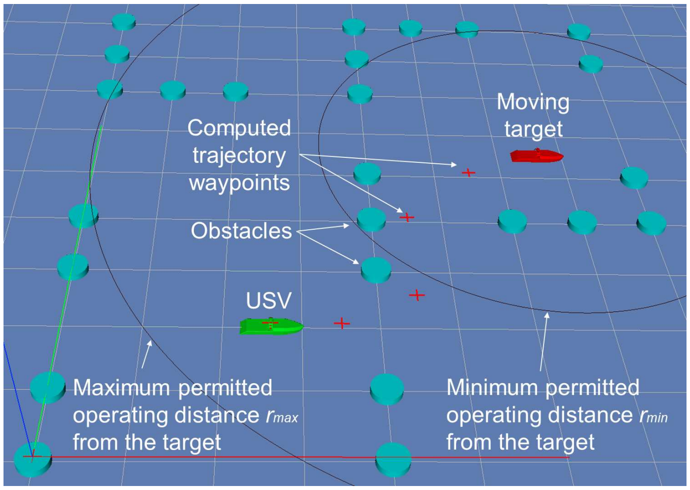

Figure 1: Following a moving target amid obstacles by an autonomous unmanned surface vehicle (USV).

distance range. The vehicle needs to maintain sufficient velocity as well as have the ability to negotiate sharp turns that could lead to deviations from its intended trajectory and thus cause possible collisions. The vehicle's following capability is inherently influenced by its own motion constraints, the motion of the target, limited sensing, and by the dynamics and complexity of the sea environment. The motion characteristics of the moving target depend on its minimum turning radius, maximum velocity, and acceleration. In addition, the complexity of the operating space may prohibit the USV to take the same trajectory as the trajectory of the target being followed. Instead, it may need to a find a different, possibly more efficient and less risky trajectory in order to keep the target within the specified distance and still avoid collisions. Hence, utilization of manually developed and tuned control rules usually does not lead to sufficiently efficient and safe follow strategies in complex environments.

To solve the above mentioned issues effectively, we have developed an approach for following a moving target amid obstacles while considering differential constraints of the vehicle and the complexity of the environment. We developed a planner that can efficiently find a trajectory to a suitable location in a close vicinity to the target that is represented as a motion goal. The motion goal is a location at which the vehicle can maximize its future chance to successfully follow the target. This is crucial since given the context of the environment and the velocity constraints of the moving target, the planner can make proficient guesses about what the pose of the target will be within a specified time horizon. In this way, the planner is capable of balanced target following that is not overly conservative but still minimizes the probability of collisions to allow the vehicle to successfully fulfill its task.

The developed planner is model-predictive [8] and incorporates A* based heuristic search [9] to efficiently find a dynamically feasible, collision-free, nominal trajectory that is composed from a sequence of explicitly designed control actions also known as motion primitives or maneuvers. In order to keep the search feasible but still flexible to comply with the task requirements, the state-action space is discretized into states that incorporate position and orientation state variables. During the search, the resolution optimal nominal trajectory is gradually expanded towards the target. Hence, only the necessary control actions are checked for collisions.

In order to minimize the execution time, maximize the tracking precision, and still make the planning feasible, each control action connecting two neighboring states encompasses a maximum velocity with which it can be executed. Sharper maneuvers are assigned smaller maximum velocity to optimize execution time and safety. In this way, the planner by the use of its cost function is capable of making decisions whether it would be more beneficial to suggest a shorter nominal trajectory with many sharp turns or a longer trajectory with fewer turns to the vehicle in a given context. The trajectory planner replans the trajectory in case its continuity is corrupted due to a sudden unexpected occurrence of dynamic obstacles. On the lower level, the trajectory is executed by the trajectory following controller to efficiently follow waypoints that make up the nominal trajectory. By the use of the implemented position control, the vehicle is thus capable of rejecting possible disturbances due to ocean waves (provided that the sea state is 2 or lower). In this way, the vehicle can safely reach its motion goal and thus successfully accomplish the mission task.

The overall approach is based on the developed USV system architecture (see Figure 2) that encapsulates all the necessary components for planning. This includes computing the motion goal, trajectory planning to the motion goal, and a feedback controller for trajectory execution. We developed a simplified version of 6 degrees of freedom dynamics model of the USV [10, 11] to be able to test the approach in a high-fidelity simulation environment in real-time. This allows for simulation of realistic boat dynamics to test the capability of the vehicle to follow the nominal trajectory in various sea states [11]. We utilized the developed model to design a realistic control action set for trajectory planning. From our previous work, we adapted an efficient lattice-based representation of the search space for the follow target task [12]. We designed a follow behavior to be able to compute a resolution optimal trajectory to a specified motion goal. Finally, we evaluated the developed approach in a high fidelity simulation environment and built a physical setup for future experiments.

RELATED WORK

The task of following a moving target in an environment with obstacles is closely related to approaches for control, trajectory tracking, and obstacle avoidance.

A basic guidance and control system of the autonomous USV prototype CNR-ISSIA Charlie is presented in [13]. The work demonstrates the effectiveness of extended Kalman filter and simple PID guidance and control laws to perform basic control tasks such as auto-heading, auto-speed, and straight line following. Similarly, a simple PID guidance was also implemented on the MIT developed SCOUT kayak platform [14]. The navigation system was further extended by incorporating the distributed autonomy architecture for sensor adaptive control of USVs in an autonomous oceanographic sampling scenario [15]. The architecture combines a behavior-based multiple objective function control model with the distributed autonomy architecture. The behavior coordination is based on the Interval Programming (IP) model. This allows reactive control in a complex environment with multiple constraints. The architecture implements the waypoint, stationKeep, constantSpeed, and the Timer behaviors. More advanced control systems exist such as, for example, the autopilot of the MESSIN system presented in [16] that can carry out automatic course tracking, initiation of a standard maneuver like a U-turn and waypoint navigation. In addition, the system is able to generate complex maneuvers for target searching and target tracking, complicated docking maneuvers, and reactive collision avoidance maneuvers and is able to react with different emergency programs to failures of any single component. The planned path is a combination of basic track units representing waypoint navigation polygonal sequences and circular arcs with high accuracy. Lot of research has been done in the area of the underactuated controller design for USVs that utilize 3-DOF simplified models, which neglect the rolling, pitching, and heaving motions [17–22].

Development of trajectory following techniques was mostly inspired by the techniques used for ground robots. In trajectory tracking, the vehicle is supposed to minimize the distance between itself and the path as well as make its heading tangential to the path. In most applications, the vehicle executes path following where the velocity profiles are specified by the user, e.g. [23]. This is in contrast to more complex trajectory tracking where the vehicle is required to reach waypoints at specific times. The Springer USV as described in [24] was designed for environmental monitoring, pollutant tracking, and also as a test bed platform for other scientific projects. The work highlights the design of a navigation, guidance, and control system of the Springer vehicle. For a basic guidance of the vehicle, simple line-of-sight and waypoint navigation techniques are used. However, advanced tracing techniques are utilized for environmental monitoring such as detecting the source of a chemical discharge. Another work related to the automatic marine data acquisition using a surface vehicle is presented in [25]. It describes the navigation, guidance, control systems, and the mission control system of the DELFIM USV developed at ISR/IST. The DELFIM USV is capable of maneuvering autonomously and performing trajectory and path following. As far as the waypoint navigation, SPAWAR Systems Center's navigation system [26] implements the standard follow-the-carrot (goal) technique. The system also contains CMU Morphin based local obstacle avoidance planner [27].

Currently, the built-in navigation planners of USVs employ global and local obstacle avoidance (OA) modules to ensure safe movement between manually specified waypoints. Some systems are capable of computing new waypoints or employ a few emergency actions, such as *abort* and *stop*, in response to fault conditions. The autonomous collision avoidance systems, particularly for USVs operating in dynamic environments, are currently very immature. They tend to rely on operator intervention in case of possible collision threats [1]. The Space and Naval Warfare Systems Center at San Diego developed a high level approach to autonomous navigation and obstacle avoidance [26, 28]. Planning around stationary obstacles is made possible using standard heuristic graph search algorithms over a simple occupancy grid. Planning around dynamic obstacles utilizes a combination of the Velocity Obstacle method [29] and a technique for computing critical points in areas, which moving obstacles could occupy along their future paths. The autonomy is limited as the user is required to stay in the control loop at all times in the deliberative obstacle avoidance process. So far, the actual demonstration in the water has only included far-field obstacle avoidance and path planning using a radar. A three layered architecture for Dijkstra algorithm based global planning and A* based local planning is presented by Casalino *et al.* [30]. They used a simple kinematic model without consideration of environmental disturbances. Benjamin *et al.* developed a technique for collision avoidance and navigation of marine vehicles respecting the rules of the roads [31]. Soltan *et al.* developed a non-linear sliding mode control based trajectory planner for a 3-DOF dynamics model [32]. Xu *et al.* reported a receding horizon control based trajectory replanning approach in which the global plan is determined using predetermined level sets from experimental runs [33].

At a higher level, the Jet Propulsion Laboratory (JPL) has developed the Control Architecture for Robotic Agent Command and Sensing (CARACaS) system [34] that utilizes algorithms used on the Mars Exploration Rover (MER) and the Earth Observation 1 (EO1) Sciencecraft Orbiter to provide a control capability for USVs. This is the most comprehensive system to the date that includes extensive demonstrations of the capabilities of the system in water. The CARACaS system consists of dynamic planning, behavior, and perception engines. The system is capable of reacting to unanticipated occurrences of obstacles using reactive behaviors within a predictable time frame. The dynamic planning engine utilizes the planner CASPER developed by JPL. The system implements fault tolerance and its functionality was tested in a series of in-water demonstrations. In 2006, re-planning capabilities of CASPER were tested by simulating failures in the system. Tests in 2007/2008 were focused on static and dynamic obstacle detection and avoidance with the aid of dual stereo cameras [35].

PROBLEM FORMULATION

Given, (1) a finite non-empty state space X, (2) the current state $x_U = [x, y, \theta, v]^T$ of the USV, where (x, y, θ) is its pose and v is the surge speed, (3) a control action space $U(x)$ for each state $x \in X$, (4) a potential flow based 6 degrees of freedom dynamics based state transition model $\dot{x} = f_U(x, u)$ of the USV [11], where $u \in U$ is a control action, (5) the state $x_T = [x, y, \theta, v]^T$ of a moving target, and (6) an obstacle map Ω such that $\Omega(x) = 1$ if x is inside an obstacle, $\Omega(x) = 0$ if x is outside an obstacle.

Compute a dynamically feasible, collision-free trajectory τ that minimizes the state transition time (in respect to the user-specified planning resolution) between the current state x_U of the USV and the motion goal $x_G = [x, y, \theta, v]^T$. The motion goal is positioned within a user-specified distance range $[r_{min}, r_{max}]$ from the target based on its predicted motion. The motion goal and the trajectory are required to be recomputed in each planning cycle to keep track of the moving target, handle dynamic obstacles and pose errors introduced due to interactions with the ocean environment. We assume that we have close-to-perfect state information because of the utilization of filtering techniques [36] for state estimation.

APPROACH

Figure 2 shows the system architecture of the approach discussed in this paper. The system architecture consists of behavior planning, trajectory planning, and waypoint following control layers. The behavior planning layer returns a suitable location around the moving target in the form of a motion goal x_G for the USV to reach. The motion goal is decided based on the obstacle map Ω of the environment and the state x_T of the target as provided by the sensors of the vehicle. The trajectory planning layer receives the motion goal and computes a collision-free trajectory represented as a sequence of waypoints to the goal. Finally, the waypoint following layer determines appropriate velocity profile for the vehicle to reliably go through the waypoints and sends commands (i.e., required throttle and rudder positions) to the low-level controllers of the USV to navigate the vehicle.

As illustrated in Figure 1, the follow behavior generates a motion goal for the USV to reach the desired pose with a predefined velocity. The motion goal is computed based on the state x_T of the target and environmental constraints. The follow behavior estimates the state of the target within future planning steps. Based on this estimation, the USV can maximize its chances of successfully following the target in further planning.

In the developed approach, trajectory planning and execution is divided into two phases. In the first phase we search 3D lattice space [8, 12] (see Figure 3) defined over a pose space

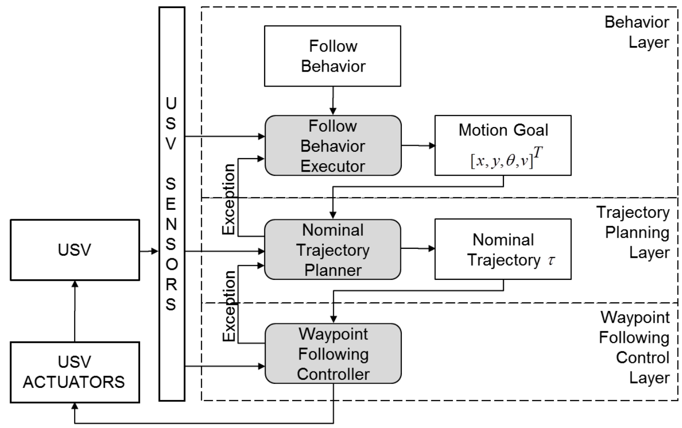

Figure 2: Developed USV system architecture for following a moving target in a marine environment with obstacles.

$[x, y, \theta]$ to acquire a nominal trajectory, while in the second phase we determine appropriate velocity profile over the generated trajectory and execute the waypoint following.

Planning Space Representation

The lattice represents a regularly sampled subset $S \subset X$ and as such makes the planning feasible in real-time. Each lattice state $s = [x, y, \theta]^T \in S$ (also termed as a lattice node) is a projection of its corresponding state $x = [x, y, \theta, v]^T \in X$ by omitting the velocity component. As is shown in Figure 3, the lattice consists of multiple XY planning layers representing 2D planning spaces with a fixed orientation θ of the USV.

We construct a discretized control action set $U = \{u_1, \ldots, u_m\}$ (see Figure 5 for an example) in which each control action $u_i \in U$ represents an edge between two neighboring lattice nodes. We represent u_i by surge velocity (see Figure 4) and heading angle profiles to consider the dynamics of the vehicle. In order to minimize the execution time, maximize the tracking precision, and still make the planning tractable, each control action encompasses a maximum velocity $u_{i,vmax}$ with which it can be executed. In this way, a control action can be reliably executed by the USV under a given sea state (i.e., does not allow substantial deviations that can lead to collisions). In general, sharp control actions should be assigned smaller maximum velocity and vice versa. Hence, the planner by the sole use of its cost function is capable to decide between a short nominal trajectory with many sharp turns and a longer one with fewer turns for a given environment. During the actual execution of the trajectory, the maximum velocity of each control action in the sequence is adjusted by the lower-level waypoint following controller as discussed further in the text. Furthermore, roll, pitch, and angular velocities are suppressed to make the planning manageable.

It is necessary to appropriately design the control action set

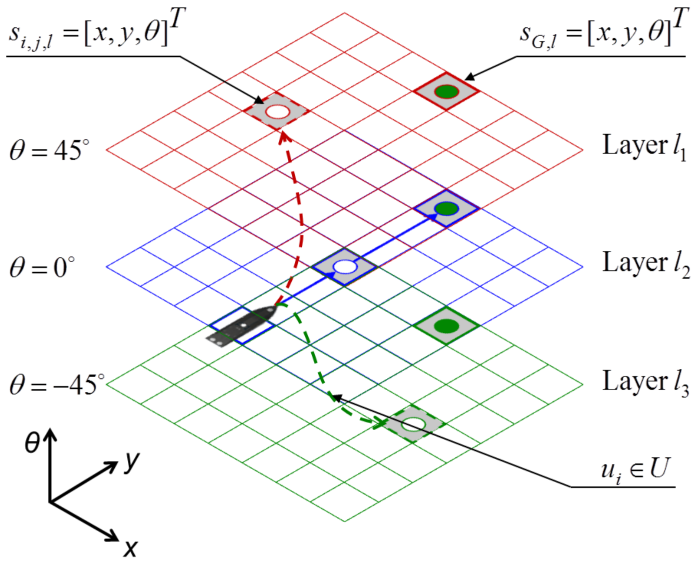

Figure 3: Planning space representation.

U (i.e., the number, type, and duration of the control actions) such that the required efficiency as well as the quality of the nominal trajectory is achieved. In our approach, we manually designed the control action set using 6 degrees of freedom simulation model of the USV [10, 12, 37]. The simulator is based on the potential flow theory [11] and is used for estimation of execution reliability of control actions under various sea states. Within the simulator, the omnidirectional ocean waves are generated by superimposing wave components that are initialized using uniformly random phase lags. In order to run the simulator in real-time, in our previous work, we developed physics-preserving model simplification techniques based on clustering, temporal coherence, and parallelization approaches [10]. We utilized a PID controller to generate each control action, however, gradient-based optimization techniques [9] can also be used to generate more complex actions. The control action set can also be generated automatically using special techniques [38] that attempt to balance between the computational efficiency and quality of the generated trajectories.

Nominal Trajectory Planning

In the first phase of the trajectory planning and execution, the lattice-based, model-predictive, nominal trajectory planner inputs the motion goal x_G and estimate of the vehicle's current state x_U and its surrounding environment is represented as a cost field Ω. The cost field includes the future time-projected states of obstacles. Ideally, the states of the obstacles can be estimated by tracing their time-parametrized trajectories as a sequence of Gaussian distributions [39]. The planner computes the shortest possible, collision-free, nominal trajectory τ between x_U and x_G by concatenating a-priori designed control actions U. Due to the discretization of the state X and action U spaces of the USV, there is a limited number of control actions to be applied in each lattice state $s \in S$ that altogether make the state lattice S.

The planner utilizes fast A* based heuristic search [9] over the lattice. The planner associates x_G and x_U with their closest corresponding states s_G and s_U in the lattice S. The nodes of the lattice are incrementally expanded towards s_G in the least-cost fashion according to $f(s) = g(s) + h(s)$, where $f(s)$ is the cost of the trajectory between s_U and s_G leading through the state s, $g(s)$ is the optimal cost-to-come from s_U to s, and $h(s)$ is the heuristic for trajectory cost estimation between s and s_G. The heuristic function $h(s)$ reduces the total number of expanded nodes in the lattice as per the A* graph search algorithm that guarantees optimality of the computed plan. The heuristic, however, has to be admissible, i.e. it is not allowed to overestimate the true cost to the goal. This ensures that only the necessary control actions are checked for possible collisions, which substantially limits the computational requirements.

The trajectory is computed in respect to the execution time objective. Hence, the cost-to-come $g(s)$ represents the total time T needed to move to state s from s_U and is computed as $T = \sum_{k=1}^{K} l(u_k)$ over K planning stages, where $l(u_k)$ is the execution time of the control action $u_k \in U$. If the control action u takes the vehicle to a collision state s_{col} (i.e., the state for which $\Omega(s_{col} = 1$ holds), then $l(u)$ is set to ∞. Similarly, the heuristic $h(s)$ returns expected time of arrival to s_G. In our approach, we compute the arrival time based on the Euclidean distance to s_G and maximum velocity of the USV. Alternatively, according to [8], one can precompute a heuristic map with optimal time execution estimates.

The computed trajectory τ consists of a sequence $\{u_1, u_2, \ldots, u_K\}$ of predefined, atomic control actions, where $u_k \in U$ for $k = 1, \ldots, K$. This sequence of control actions is then translated into a sequence of $K+1$ number of waypoints $\{w_1, \ldots, w_{K+1}\}$ leading to the motion goal s_G. The nominal trajectory complies with the dynamics of the vehicle, i.e., guarantees that the USV will be able to progressively reach the waypoints in a sequence without substantial deviations that can lead to collisions.

Nominal Trajectory Execution

We utilize a waypoint following controller to ensure a robust and efficient execution of the trajectory. The controller drives the USV from one waypoint to the next without any need to consider obstacles (as the transitions between consecutive waypoints are guaranteed to be collision-free). We utilize waypoints as a means for position feedback control and as such can be partially used for compensating possible disturbances due to ocean waves. For high sea states, different technique needs to be used such

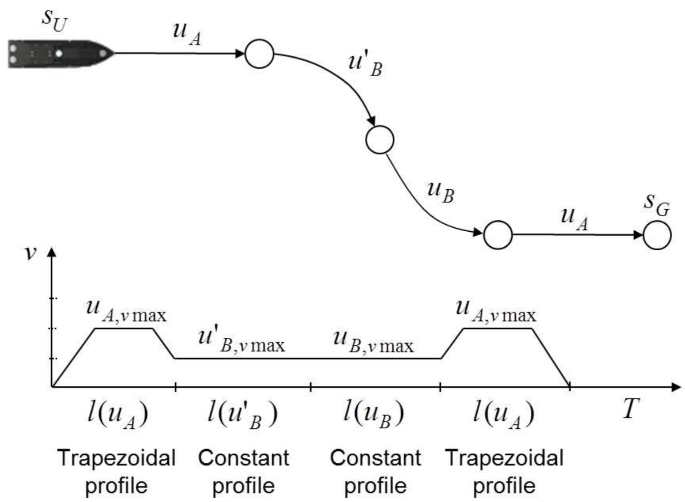

Figure 4: Examples of velocity profiles assigned to control actions.

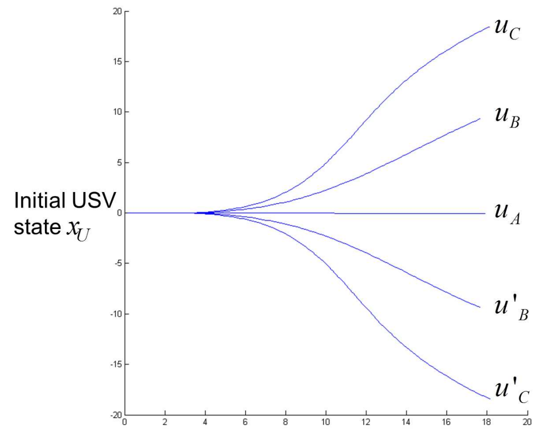

Figure 5: Control action set used in the experiment.

as [12, 37] in order to handle the disturbances in the planning stage. In the implemented version of the waypoint following, the vehicle employs PID controller to determine steering action such that it minimizes the angle between its heading and the direction to the waypoint. The acceptance radius around each waypoint is defined by the user of the system based on the configuration of the environment. Each waypoint is required to be reached with a specified velocity. Hence, the controller determines the appropriate velocity based on the velocity profiles (see Figure 4) of individual control actions that make up the nominal trajectory. The velocity is then controlled using a PID controller. The controller outputs appropriate throttle and rudder positions for the lower-level controller that further converts it to actuator actions. During execution of the trajectory, an exception occurs if the vehicle loses its chance to successfully reach the desired waypoint. In that case, the trajectory is immediately recomputed by the vehicle's control and planning system.

RESULTS

In the designed experiment, an autonomous surface vehicle was supposed to follow a human-driven boat within a user-specified distance range $r_{min} = 50$ m and $r_{max} = 100$ m in a simulated environment with obstacles. We assumed that the USV had a complete map of the environment. The developed planner was utilized to find the shortest possible, dynamically feasible trajectory amid obstacles to approach the target with a given velocity and orientation. During the experiment, we manually drove one of the boats and let the autonomous USV follow the boat. Figure 6 shows a sequence of planning situations that arose during the execution of the follow task. In most of the situations, the USV follows the same trajectory as the target boat. However, the situation (d) illustrates a case in which the USV estimates the future position of the target boat and chooses a different trajectory to approach the target. The USV determines a motion goal by simply projecting the current state of the target boat into future based on its current velocity and heading. This particular scenario shows that in some situations it may not be the best strategy to directly follow the human-driven boat. It is rather beneficial to find a different, more effective trajectory. The experiment shows that the developed system is able to compute and reliably execute the nominal trajectory. By using the current version of the system, the average computation time of a trajectory with the length of approximately 75 m in the designed planning space is 3 s on a computer with Intel(R) Core(TM) i7-2600 CPU @ 3.4GHz processor. In the underlying planning space lattice representation, the dimension of each grid cell was chosen to be 7.5 m. The orientation of the vehicle was discretized into four different layers.

For the experiment, we designed a control action set for the USV as illustrated in Figure 5. It contains 5 control actions u_A, u_B, u_C (and their symmetric counterparts u'_B and u'_C) with different final orientations $u_{A,\theta} = 0$ rad, $u_{B,\theta} = 0.523$ rad, $u_{C,\theta} = 0.872$ rad, and positions $u_{A,f} = [18,0]^T$ m, $u_{B,f} = [18,9]^T$ m, $u_{C,f} = [18,18]^T$ m. The control actions were manually determined based on the dimension of the boat ($12 \times 4 \times 4$ m) and the obstacle density of the experimental environment. We specified the final orientation as well as position for each control action and employed a PID controller to validate the dynamical feasibility of the control action in the simulator. In addition, we set the maximum velocity to be 3 m/s for all the control actions.

The developed simulation environment offers a 3D world by implementing physics based scene, incorporating rigid body dynamics, and supports static as well as dynamic obstacles. The

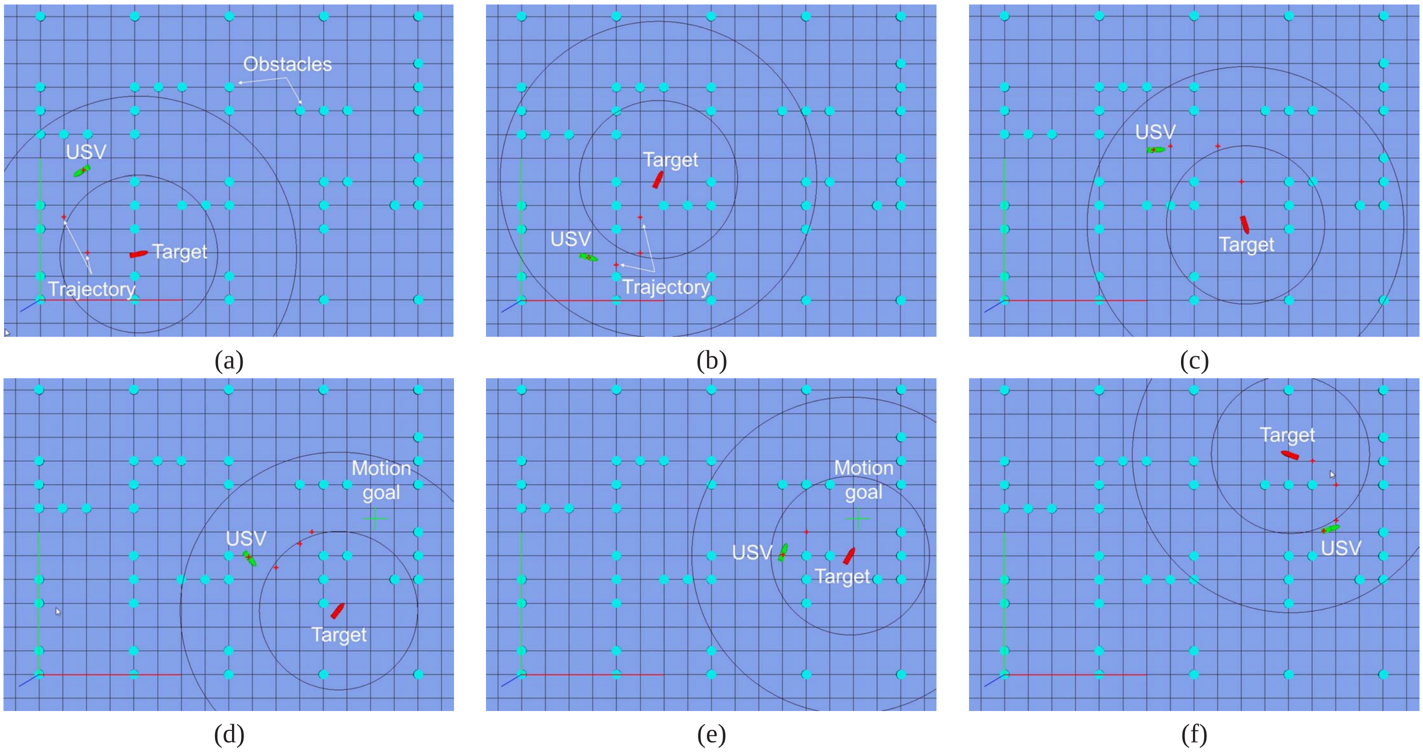

Figure 6: Experimental result of follow behavior execution by an autonomous unmanned surface vehicle.

environment is capable of supporting multiple different vehicles. In the simulator, the target boat can be driven by the user of the system. The vehicles are represented with 3D models created using a CAD tool. The variety of vehicle models and obstacles can be possibly included to allow us to run simulations in realistic conditions and environments. In the developed simulator, the implemented USV dynamics model responds to ocean waves configured by the user. In this way, the developed approach for following a moving target could be thoroughly evaluated in the environment with variously positioned obstacles.

Finally, we developed a physical setup (see Figure 7) for future evaluation of the designed approach for target following. The evaluation will be conducted using two radio controlled boats in a 50 foot wide tank within the Neutral Buoyancy Research Facility at the University of Maryland. In the current version of the setup, the autonomous boat can be remotely controlled by the developed navigation and control software as a part of the system architecture (see Figure 2) consisting of behavior and trajectory planning, and waypoint following layers running on a laptop. The positions of the boats as well as the positions of obstacles are perceived using a vision system consisting of a single fish eye lens camera mounted on ceiling. The camera is calibrated using a developed calibration module. Calculating much of the calibration data is done automatically, and a mechanism is provided for changing the tracking attributes dynamically. We have developed color blob detection image processing algorithms for tracking of the boats and obstacles. The uncertainty in vision will be compensated by the extended Kalman filter [36]. We will utilize PCTX interface between the laptop and a transmitter to allow radio transmission of actuator commands to control the throttle and rudder positions of the autonomous boat. The setup will allows us to manually drive one of the boat using a remote controller. We will let the autonomous boat follow the human-driven boat. The control action set will be modified to accommodate the smaller dimension of the radio controlled boat. The maximum velocities for all control actions will be determined by running experiments using the physical boat.

CONCLUSIONS AND FUTURE WORK

In this paper, we developed a general trajectory planning approach for an autonomous surface vehicle to follow a dynamically changing motion goal in an environment with obstacles. We specifically focused on the task of following a moving target boat. The USV is supposed to follow the target within a user-specified distance range. The developed approach is based on lattice-based trajectory planning that is capable of computing trajectories, which balance their execution efficiency and relia-

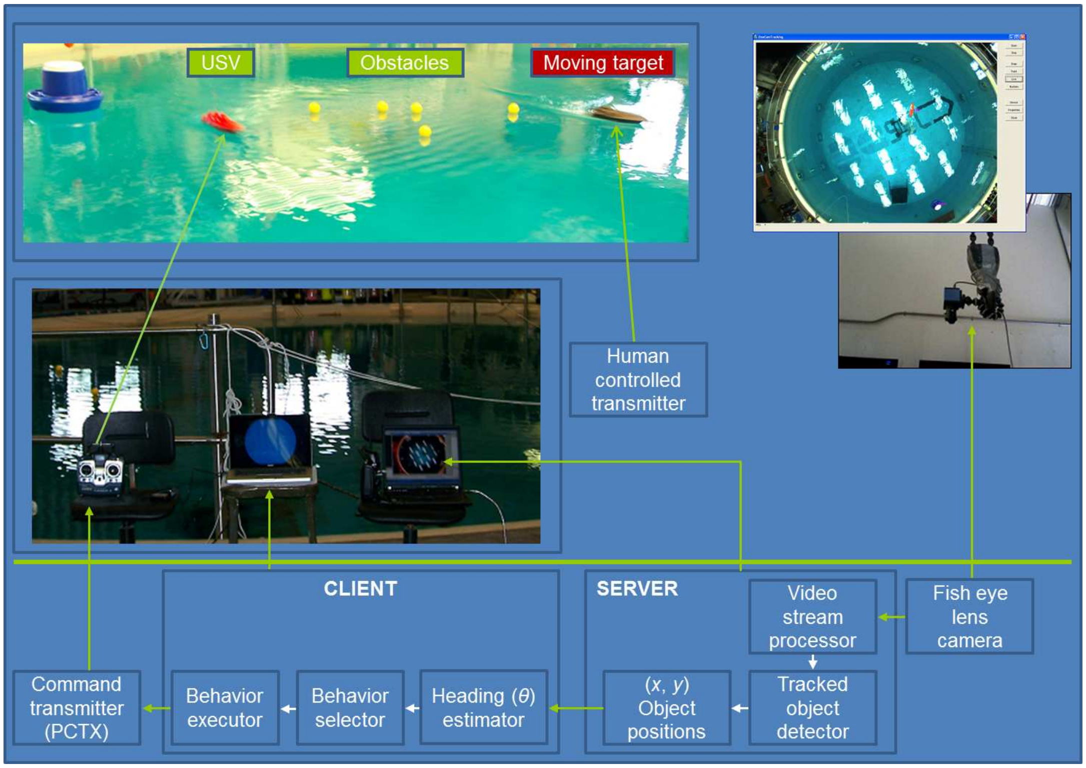

Figure 7: Developed a physical setup for testing autonomous behaviors in the Neutral Buoyancy Research Facility (NBRF) at the University of Maryland.

bility to minimize the probability of collisions with obstacles. The planner considers the USV dynamics directly in the planning process so that the generated trajectory complies with the differential constraints of the vehicle. In the designed experiment, we have shown the capabilities of the planner to compute dynamically feasible trajectories to follow a moving target in a simulated, complex environment with obstacles. In addition to the simulation environment, we have developed a physical setup that will be used for future evaluation of the approach by running target following experiments using radio controlled boats.

The future desired pose of the USV in the form of a motion goal is currently determined by a simple heuristic algorithm for future projection of the target's state. However, our future plan is to extend the developed trajectory planning approach by a sophisticated motion goal computation technique based on our previous work [40] to be able to make proficient guesses where the target may be within a specified number of planning steps. This will include development of a probabilistic behavior model of the target boat. Furthermore, the discretization of the control action set limits the flexibility of the planning process. Hence, we would like to enhance the planner by locally optimizing the control actions during the actual search in the lattice. Finally, we plan to cope with motion uncertainty in the follow task by incorporating previously developed MDP based and heuristic planning approaches by our group [12, 37]. The same holds for handling the sensing uncertainty which is necessary for operation in a real environment in which the vehicle needs to account for partial observability of its own state as well as the state of the target. The uncertainty in sensing of the target varies depending on the weather conditions and dimensions of the target. Hence, it is necessary to consider the effect the partial observability has on the operation of the USV in the simulation. We plan to incorporate a sensor uncertainty model into the USV simulation so that we can simulate the effect of the environment on the estimation of states of the target in the sea. In addition, in this paper, we assume that the USV has a complete map of the environment. In future work, we will incorporate the capability for the planner to deal with partially observable environment.

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