

A Hierarchical Control and Obstacle Avoidance System for Unmanned Sea Surface Vehicles

P. Krishnamurthy and F. Khorrami

Abstract— In this paper, the development of a hierarchical control, path planning, and obstacle avoidance system for autonomous operation of Unmanned Sea Surface Vehicles (USSVs) in uncertain cluttered environments (e.g., littoral environments) is described. The system is designed with a modular structure incorporating a robust inner-loop controller and a hierarchical combination of wide-area, intermediate-area, and local-area planning and obstacle avoidance algorithms. The performance of the proposed system has been demonstrated through Hardware-In-The-Loop (HITL) and experimental tests. The HITL simulation platform incorporates detailed dynamics of the USSV including hydrodynamic effects as well as emulation of sensors and instrumentation onboard the USSV including Radar. The HITL platform can simultaneously simulate multiple USSVs and passive obstacles and provides the computer which runs the controls and obstacle avoidance algorithms with the exact environment which it sees when operating in the experimental USSV testbed.

I. INTRODUCTION

Unmanned vehicles and mobile robots have the potential to play a vital role in a wide variety of application scenarios and offer an effective solution for automating routine, repetitive, or dangerous tasks. The efficacy and applicability of unmanned vehicles is greatly enhanced by increasing the level of autonomy of the mobile agent. In particular, a key technology for unmanned vehicles is a robust perception and obstacle avoidance system for operation in complex uncertain and cluttered environments such as littoral environments. In this paper, we describe the design and implementation of a hierarchical Maritime Seaway Navigation System (MSNS) for control, path planning, and obstacle avoidance for Unmanned Sea Surface Vehicles (USSVs). The various civilian and military applications of USSVs are well-recognized and their control and navigation problems have been studied in the literature [1]–[12]. The MSNS is designed with a modular architecture incorporating two core subsystems: (a) USSV-NAV, a high-performance robust tracking and stabilization control system; (b) USSV-CAS, a computationally efficient real-time Collision Avoidance System (CAS) comprised of a hierarchical combination of path planning and obstacle avoidance algorithms. The USSV-NAV design utilizes a robust nonlinear dynamic controller [8] based on a six degree of freedom (6DOF) nonlinear dynamic model for USSVs taking into consideration disturbances due to waves, wind, and ocean currents and addresses multiple control objectives including trajectory/waypoint tracking and stabilization. The USSV-CAS, which provides a path planning and obstacle avoidance system (OAS) is designed with a hierarchical architecture incorporating graph-search based wide area and intermediate area planners and a GODZILA-based local area planner [15] to yield computationally efficient and robust planning and obstacle avoidance in complex uncertain cluttered environments.

A high-fidelity Hardware-In-The-Loop (HITL) simulation platform has been developed to evaluate and demonstrate the

The authors are with FarCo Technologies, Inc., Brooklyn, NY, USA, and the Control/Robotics Research Laboratory (CRRL), Dept. of ECE, Polytechnic Institute of NYU, Brooklyn, NY, USA. This work was supported in part by the Office of Naval Research (ONR) under contract Nos. N00014-04-M-0181 and N00014-06-C-0051. Corresponding author: F. Khorrami, khorrami@smart.poly.edu.

MSNS performance. The MSNS has also been demonstrated on experimental USSV testbeds. The development of the HITL platform for testing of the obstacle avoidance system is based on the 6DOF USSV dynamic model in [7] and the controls-oriented HITL testbed in [8], [9] which offers an emulation of the instrumentation onboard the USSV including sensors and actuators and the interface to these hardware components through a Controller Area Network (CAN) bus. The HITL simulation platform described in this paper additionally incorporates a detailed model of a Radar system and its interface characteristics to provide the computer which runs the controls and obstacle avoidance software with the exact environment which it sees when operating in the experimental USSV testbed.

This paper is organized as follows. The architecture of the hierarchical MSNS and its principal constituent components are described in Section II. The experimental setup and the HITL simulation platform are described in Section III. HITL simulation and experimental studies of the proposed hierarchical obstacle avoidance system are discussed in Section IV.

II. HIERARCHICAL CONTROL AND OBSTACLE AVOIDANCE SYSTEM

The MSNS addresses both inner-loop control and obstacle avoidance and has the overall architecture illustrated in Figures 1 and 2. The sensor data collected during operation are processed through a suite of algorithms including Kalman filtering, inertial navigation, and Radar data processing to estimate both the translational and rotational states of the USSV and the obstacle geometry of the operating environment. A multi-resolution hierarchical approach is utilized in MSNS for robust, reliable, and computationally efficient path planning and obstacle avoidance over wide geographical areas and cluttered environments. The core of the MSNS includes the following components interconnected in a hierarchical structure as shown in Figure 2:

- A collision avoidance system (USSV-CAS) comprising of a hierarchical combination of path planning and obstacle avoidance algorithms for computationally efficient real-time planning in complex cluttered environments. As shown in Figure 2, the path planning and obstacle avoidance system in MSNS incorporates the following sub-components: a Wide-Area Planner (WAP) based on a graph theory algorithm; an optional Intermediate-Area Planner (IAP) based on maneuver optimization (taking into account motion capabilities of the specific USSV); a Local-Area Planner (LAP) based on the GODZILA obstacle avoidance algorithm. Given a desired vehicle trajectory (specified as a sequence of desired locations by a manual operator or a high-level mission planner), the objective of the OAS is to track the desired vehicle trajectory as closely as possible while avoiding obstacles. For environments with relatively sparse obstacle geometries (i.e., not maze-like), the LAP is sufficient to ensure safe obstacle avoidance. The IAP and WAP add a higher degree of robustness to the path planning and obstacle avoidance behavior in complex environments and also add more flexibility in terms of being able to simultaneously address other kinematic objectives and/or to achieve specific types of behaviors.

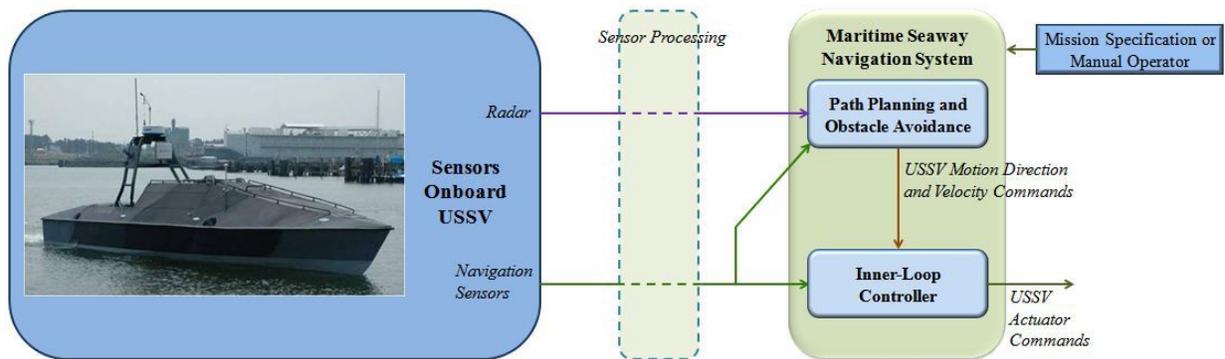


Fig. 1: Architecture of the MSNS: USSV-NAV (inner-loop controller) + USSV-CAS (path planning and obstacle avoidance system). The U. S. Navy USSV-HTF (High Tow Force) shown in inset in the figure.

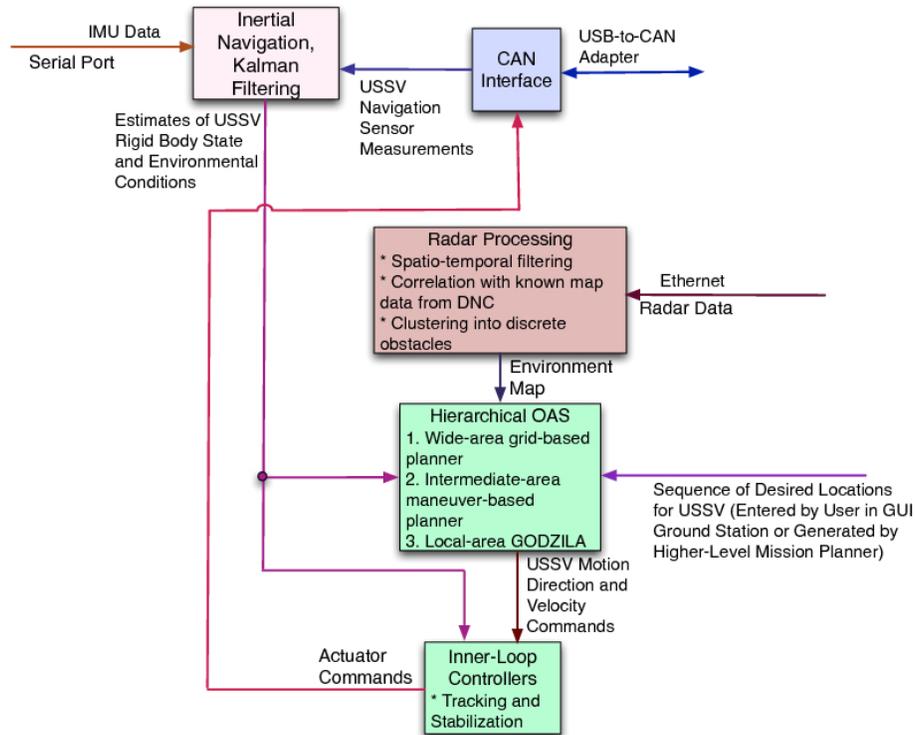


Fig. 2: The MSNS hierarchical control and obstacle avoidance system.

- A set of inner-loop robust nonlinear dynamic control algorithms (USSV-NAV) for stabilization and tracking and to compute actuator commands to track the reference trajectory generated by the obstacle avoidance algorithms. In addition, as shown in Figure 2, the MSNS also integrates sensor and actuator interfaces (via CAN bus, Ethernet, and serial) and sensor processing algorithms. The WAP addresses the far-field (or global) aspect of path planning and obstacle avoidance utilizing an environment map with large range but low resolution, thus taking into account landmass as well as possibly large moving obstacles such as other ships/USSVs (stationary or moving), but not necessarily smaller obstacles such as buoys or debris which are addressed by the LAP.

The WAP is designed using a variant of a graph theory based search algorithm [13], [14] to compute the optimal trajectory from a given initial position to a given final position taking into account obstacles which are represented through an occupancy grid. The graph theory algorithm utilizes an iterative search and incorporates a heuristic. The heuristic component facilitates incorporation of a penalty for close approach to obstacles and enables finding of a trajectory solution with specific desired clearance to obstacles. An appropriate heuristic can also potentially be

applied to address specific desired behavior such as rules of the road (i.e., NAV Rules), a set of rules prescribed in COLREGS (Collision Avoidance Regulations) which specify appropriate actions in response to approach of other marine vehicles. The IAP locally filters the reference trajectory recommendation generated by the WAP to ensure feasibility of the resulting trajectory taking into account the kinematic and dynamic constraints of the specific USSV and the corresponding set of feasible maneuvers. The IAP utilizes a graph theory algorithm to optimize over a mobility graph of the vehicle. The output of the IAP is an optimal sequence of maneuvers taking into account the trajectory computed by WAP, the intermediate-area obstacle geometry, and the USSV motion capabilities. The introduction of the maneuver-based planner offers agile path planning especially in cluttered environments in close proximity to obstacles (e.g., buoys in littoral environments) by explicitly accounting for the vehicle's kinematic and dynamic capabilities to compute optimal feasible trajectories. The LAP addresses the near-field (or local) aspect of path planning and obstacle avoidance and operates at a higher sampling frequency than WAP but focuses only on avoiding local obstacles that could

be moving or too small to show up in the coarse map used by the WAP. Based on the local obstacle topology, the LAP computes the required local perturbations on the global trajectory recommendation and outputs USSV motion direction and velocity commands to the inner-loop controller which then computes the control signals for the physical actuators (rudder and propeller). The design of the LAP is based on the GODZILA algorithm [15]. GODZILA (Game Theoretic Optimal Deformable Zone with Inertia and Local Approach) is a general computationally lightweight path planning and obstacle avoidance algorithm that does not require any a priori knowledge of environment and does not rely on building of an obstacle map. GODZILA follows a purely local approach using only the sensor measurements at the current time and requiring only a small number of stored variables in memory. The low memory and computational requirements of GODZILA make it an attractive choice for small autonomous vehicles. GODZILA is applicable in any finite-dimensional environment (e.g., 2D, 3D) and guarantees convergence to the target in finite time with probability 1. GODZILA is based on three components: Optimization based on a cost that penalizes motion in directions other than the direction to the target, motion towards obstacles, and back-tracking; A local straight-line planner utilized if the target is visible; Navigation towards a random target when a local minimum or “trap” is detected.

The path planners operate based on an environment map constructed by processing the sensor data from Radar in conjunction with data from compass, Inertial Measurement Unit (IMU), GPS, etc., and also utilizing known map data from Digital Nautical Charts (DNC). The MSNS also integrates a set of Radar processing algorithms for estimating obstacle geometry and situational awareness of the discrete detected obstacles including an automated clustering algorithm to spatially and temporally identify and track discrete obstacles. The objective of Radar data processing algorithms in the context of the obstacle avoidance system is to address reduction of clutter in the collected data and construction of a situational awareness of the static and dynamic obstacles in the environment including estimation of the projected future trajectories of moving obstacles. To this end, the MSNS includes a set of spatio-temporal Radar filtering and smoothing algorithms (Figure 3) developed based on median filtering, Discrete Cosine Transform (DCT), temporal weighted sliding window memory, correlation with known map data from DNC and/or other databases, obstacle occupancy estimation within a probabilistic occupancy grid, and obstacle set decomposition into discrete obstacles via clustering of the Radar data and temporal correlation of clusters across Radar frames. These algorithms enable spatio-temporal identification and tracking of discrete obstacles and would potentially facilitate implementation of full NAV Rules compliance capabilities. The Radar data is obtained as scan lines (Figure 4) which are converted into absolute frame using the ship’s position and orientation as estimated by the inertial navigation algorithms (using data from GPS, compass, IMU, etc.). The Radar data are then filtered spatially to reduce clutter and thereafter temporally wherein regions corresponding to high Radar echoes in multiple successive frames are weighted higher as being more likely to contain an obstacle. The spatial and temporal filtering utilize customizable weighting factors tuned based on weather conditions. The filtered Radar data are correlated with the DNC data (Figure 5) available from the National Geospatial-Intelligence Agency (NGA). The DNC data are available as multiple layers corresponding to coast line, buoys, markers, etc. These layers have been combined and

integrated into a single database used both for obstacle avoidance and for HITL simulation. The Radar data are correlated with the DNC data to filter land echoes and identify transient (e.g., moving obstacles such as ships, etc.) obstacles that are not contained in the DNC data. The transient obstacle set is decomposed into discrete obstacles using a clustering algorithm and the velocity of each discrete obstacle is estimated to attain a situational awareness of the static and dynamic obstacle set. The likely future trajectories of the transient obstacles are also computed from their estimated velocities and incorporated into the probabilistic occupancy grid. During the spatial and temporal filtering, the size of the Radar returns is propagated to obtain a probabilistic occupancy grid representing the likelihood of the occurrence of obstacles in cells in the grid (see Figure 6 where the probabilities are indicated through color coding as a shade between green and reddish brown with green representing less likely; the red cells are ones found on DNC). The estimated likely future trajectories of the discrete obstacles are also integrated into the grid. The probabilistic entries in the grid are utilized by the OAS modules. In the WAP and IAP (which are based on graph search), the probability of an obstacle being contained in a cell in the grid influences the traversal cost for that cell while in the GODZILA-based LAP, the obstacle occurrence probability is used in computation of the obstacle repulsion component in GODZILA’s optimization cost.

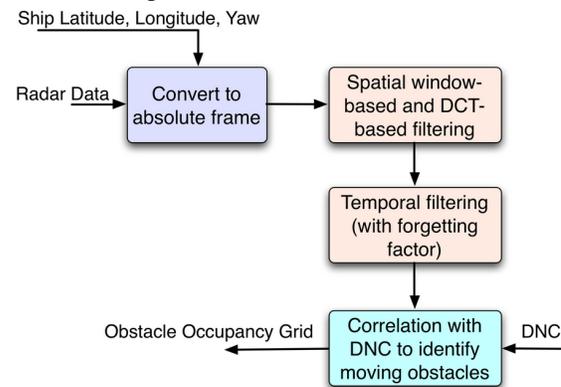


Fig. 3: Processing of Radar and DNC data.

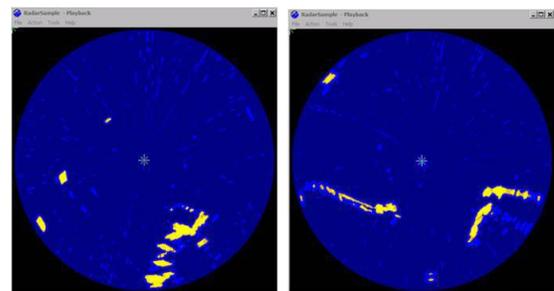


Fig. 4: Typical experimental Radar data obtained via Xenex Radar processor module.

The MSNS can utilize both Radar scan line data (in conjunction with the algorithms for stochastic spatio-temporal Radar processing for environment estimation, DNC correlation, and spatio-temporal clustering as described above) and ARPA messages generated by a third-party Radar processing module (such as the Xenex system). The hierarchical path planning and obstacle avoidance module provides commands to the USSV-NAV subsystem which consists of a bank of inner-loop nonlinear control algorithms that address tracking and stabilization objectives. USSV-NAV provides a high-performance stabilization and tracking control system based

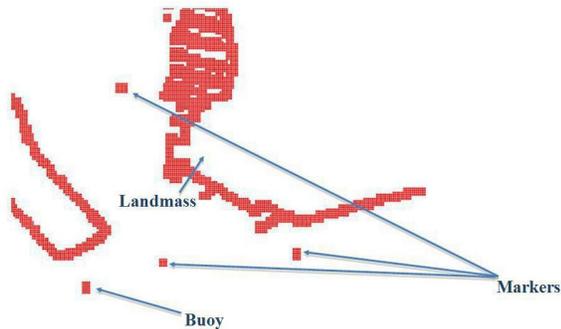


Fig. 5: Sample DNC data.

on a multi-loop gain-scheduled control architecture utilizing a nonlinear backstepping-based control design [8].

III. EXPERIMENTAL SETUP AND HITL SIMULATION PLATFORM

The HITL simulation platform incorporates a nonlinear dynamic model of the USSV [7], emulation of sensors and instrumentation onboard the USSV, and the actual hardware and software components used for control of the USSV in the experimental testbed. The dynamic model utilized incorporates detailed models of hydrodynamic effects, actuators including thrusters/propellers and control surfaces, and disturbances including ocean currents, waves, and wind. The fidelity of the USSV dynamic model and HITL platform have been tested [9] using experimental data collected from two different USSVs in the Atlantic ocean: the U. S. Navy PowerVent APTD (Advanced Propulsion Technology Demonstrator), and the U. S. Navy USSV-HTF (High Tow Force). The HITL simulation platform is designed to provide the computer which runs the controls and obstacle avoidance software with the exact environment which it sees when operating on the experimental USSV platform. The HITL simulator incorporates emulations of the instrumentation onboard the USSV including the sensors and actuators and the interface to these hardware components through a CAN bus. The HITL simulator also includes a stochastic Radar simulator interfaced via Ethernet. The HITL simulation platform provides a high-accuracy real-time testbed for development and evaluation of controllers and obstacle avoidance algorithms for USSVs. The simulated environment includes both data on static obstacle geometry from DNC and simulated dynamic obstacles (other ships/USSVs).

The hardware architecture of the experimental USSV platform is illustrated in Figure 7. The control and obstacle avoidance algorithms are implemented on a notebook computer. The sensors (except Radar) and actuators on the USSV

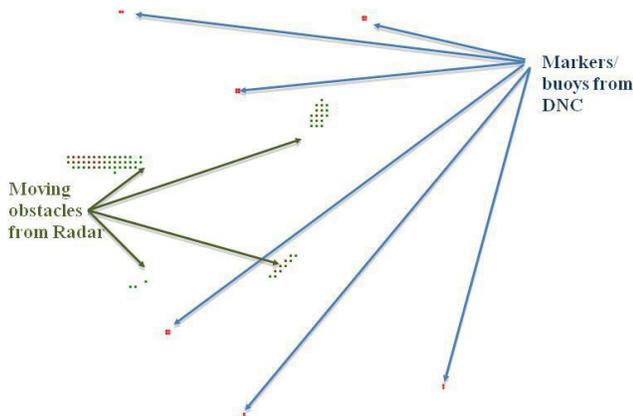


Fig. 6: Processed Radar data (as a probabilistic occupancy grid) overlaid with DNC data.

are all connected to a common high-speed CAN bus accessed via a USB-to-CAN adapter from the notebook computer. The Radar data for the OAS module is accessed via Ethernet. The available sensors on the USSV include a compass, a GPS, water speed and depth sensors, rudder position sensor, engine RPM sensor, and Radar. The available actuator inputs include rudder angle and port and starboard throttles. In addition, our avionics box (which is the same as used in our work on helicopter control [16]) is interfaced with the notebook computer via a serial port. This avionics box provides a six degree-of-freedom IMU with an update rate of 50 Hz.

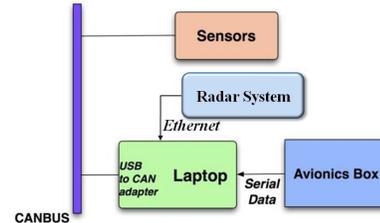


Fig. 7: Architecture of the experimental platform.

The architecture of the HITL simulation platform is illustrated in Figure 8. The HITL simulator utilizes two computers: Computer 1, which runs a real-time simulation software of USSV dynamics, sensor models, and the operating environment; Computer 2, which runs the entire MSNS, which includes the sensor data processing algorithms, the OAS algorithms, and the inner-loop control laws. Computer 2 in the HITL simulation platform is the notebook computer that is used to run control and obstacle avoidance algorithms onboard the USSV during experimental testing. The USSV dynamics simulation software on Computer 1 is designed to be flexible to facilitate run-time customization of simulated environment and USSV dynamics parameters. Computer 2 receives serial IMU data (which emulates data from the IMU in our avionics hardware) from Computer 1 with an update rate of 50 Hz. Computer 2 also interacts with Computer 1 through CAN bus and Ethernet. The software on Computer 1 includes a complete emulation of the CAN interface which is seen by Computer 2 during operation on the USSV including all sensor messages and actuator status messages with the proper formats and update rates. The software on Computer 1 receives actuator commands through the CAN interface and computes a full 6DOF dynamic simulation of the ship. The software on Computer 1 also computes a simulation of the environment geometry and Radar data. The Radar data are communicated to Computer 2 via an Ethernet port. The result of the dynamic simulation is visualized using an OpenGL GUI front-end which can be displayed on Computer 1 or can be exported to another computer via a network socket interface. The HITL simulator also includes an environment geometry server subsystem, which incorporates data from DNC and a model of the Radar including its noise characteristics. The simulator also supports both “natural” (maps from DNC data) and “artificial” (simulated environments with specified cuboidal and/or cylindrical obstacles) environments with dynamic obstacles (other ships/USSVs). As illustrated in Figure 8, the overall architecture of the HITL simulator includes the following components:

- DNC: The DNC data layers from NGA are entered into a PostgreSQL relational database. The DNC information (which forms the static obstacle geometry) for any specified region can be extracted efficiently with a database query.
- Radar: Two types of obstacle information are passed to the Radar simulator component: Static obstacle (including DNC) information within the Radar range; Locations of other ships within the Radar range, typically simulated as moving along pre-specified trajectories. The obstacle

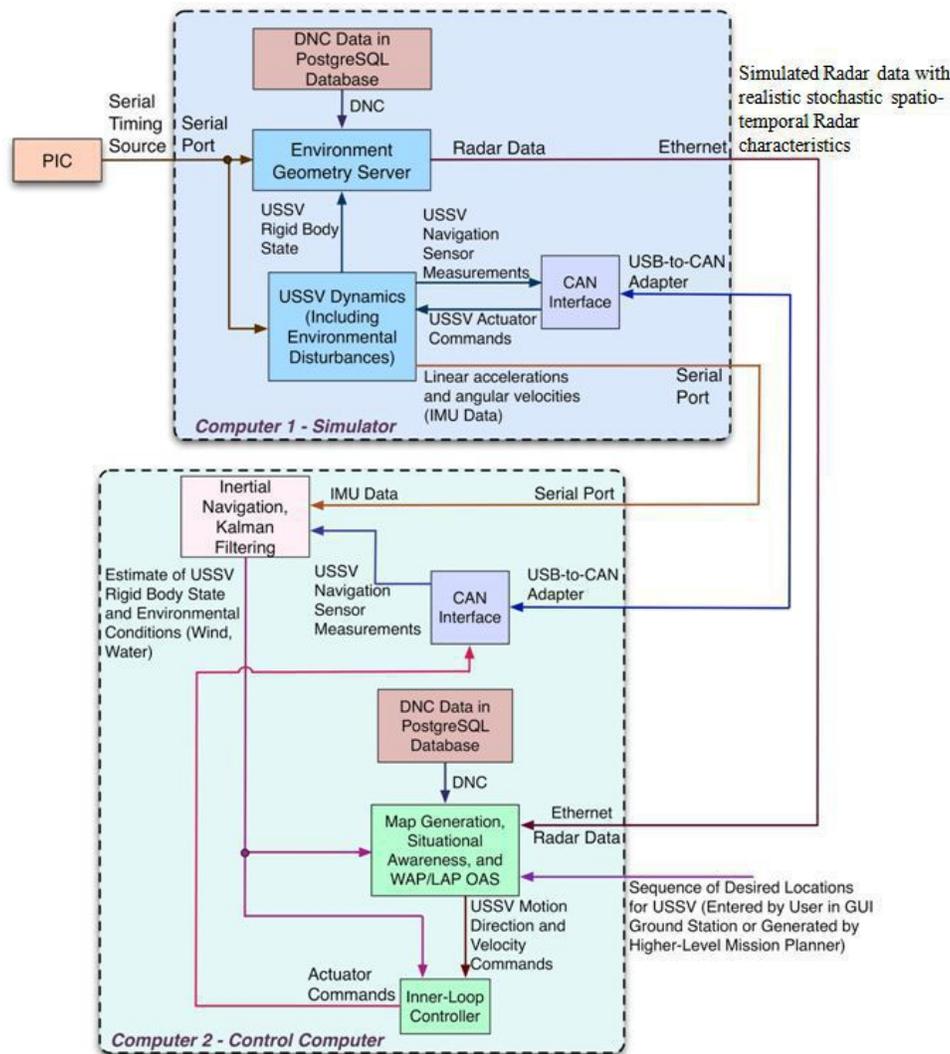


Fig. 8: Architecture of the HITL simulation platform.

information is converted into Radar scan data and transmitted to Computer 2 through a network interface. The Radar simulation is based on an empirical model of the Radar characteristics, identified from experimentally obtained Radar data (Figure 4) for both stationary and moving objects in the environment, and takes into account stochastic spatio-temporal properties of the Radar clutter and its directional characteristics. The stochastic Radar model generates physically realistic Radar data in simulations with both static and moving obstacles.

- USSV dynamics: A high-fidelity USSV dynamic simulator is utilized based on the model described in [7], which includes 6DOF rigid body dynamics, hydrodynamic forces and torques, and models of environmental disturbance effects. The simulated sensor data generated by the dynamic simulator is passed to Computer 2 through a CAN interface and a serial port (for IMU data). The actuator commands from the inner-loop controller running on Computer 2 are also received by Computer 1 through the CAN interface.
- Control computer (Computer 2): This computer runs all the sensor processing, controls, and obstacle avoidance algorithms. Typically, the GUI ground station is also run on this computer.
- PIC: used to provide an accurate timing source.

The HITL simulation platform has been designed to be able to support simultaneous simulation of multiple USSVs

(limited only by the processing, graphics, and I/O port capabilities of the computers being utilized) as well as heterogeneous behaviors of the USSVs (e.g., USSVs running MSNS, USSVs tracking pre-specified waypoints or moving along pre-defined trajectories, etc.). Furthermore, the simulation platform has been designed to be flexible so that depending on available hardware, a subset of the USSVs could be simulated in HITL mode while the dynamics of the other USSVs could be simulated purely in software (with support also for a soft HITL mode utilizing virtual CAN, serial, and Ethernet ports for communication). This feature of the HITL simulation platform facilitates development and testing of path planning and obstacle avoidance algorithms for USSV applications in cluttered environments with multiple USSVs.

IV. SIMULATION AND EXPERIMENTAL STUDIES

The performance of the proposed control and obstacle avoidance algorithms has been verified through extensive simulation studies based on the multi-USSV simulator implementation described in Section III. Simulation studies have been performed both for “natural” (maps from DNC data) and “artificial” (simulated synthetic environments with multiple cuboidal and/or cylindrical obstacles in specified configurations) environments with dynamic obstacles (other ships/USSVs). Sample screenshots from simulation studies are shown in Figures 9 and 10. Simulation studies have been performed both in single-USSV and multi-USSV scenarios

in a variety of DNC-based and synthetic environments. The robustness of the system in cluttered environments and compliance with the basic right-of-way rules have also been verified using the multi-USSV simulation platform.

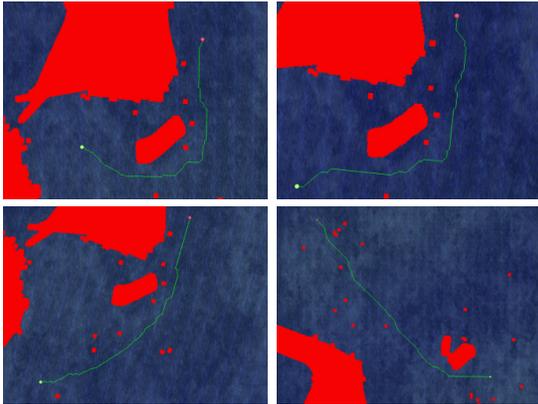


Fig. 9: Screenshots from simulation testing in DNC-based environments (Red and green circles: initial and target locations, green track: trajectory of USSV, solid red areas: obstacles from DNC).

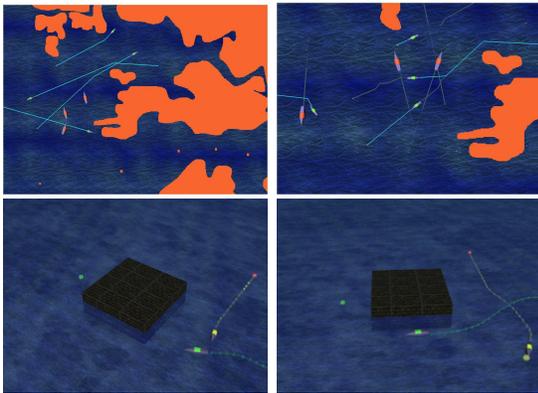


Fig. 10: Screenshots from multi-USSV obstacle avoidance simulation studies.

A sample experimental run of the control and obstacle avoidance system on the USSV-HTF is shown in Figure 11 wherein the black circle and the green circle represent the initial location and the target location, respectively, and the red “+” marks represent the obstacles in the vicinity. In this experimental run, there were no moving obstacles in the vicinity. It is seen that the obstacle avoidance system successfully routes the ship around the detected obstacles.

V. CONCLUSION

The development of an integrated hierarchical control, path planning, and obstacle avoidance system for USSVs operating in uncertain cluttered environments was described. The system has a modular structure incorporating a robust inner-loop controller and a hierarchical combination of path planning and obstacle avoidance algorithms including wide-area, intermediate-area, and local-area planners. The development of a HITL simulation platform including 6DOF dynamics and emulation of all sensors and other components on the experimental USSV testbed was also described. The performance of the proposed system was demonstrated through HITL simulation and experimental studies.

ACKNOWLEDGMENT

The authors would like to thank Dr. Robert Brizzolara of ONR for support of the effort and technical review of the manuscript. We would also like to thank Mr. Eric Hansen for his support. We would also like to record our appreciation for Jason Altice of WRSYSTEMS and Al Frontin and Sam Calabrese of NSWCCD for their on-ship support.

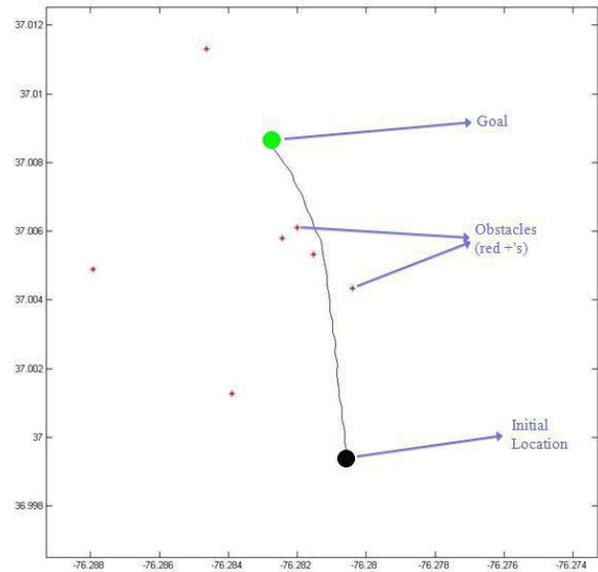


Fig. 11: Experimental testing of obstacle avoidance performance.

REFERENCES

- [1] T. I. Fossen, *Guidance and Control of Ocean Vehicles*. New York: John Wiley and Sons, 1994.
- [2] J. Goclowski and A. Gelb, “Dynamics of an automatic ship steering system,” *IEEE Trans. on Automatic Control*, vol. 11, no. 3, pp. 513–524, July 1966.
- [3] T. I. Fossen and A. Grovlen, “Nonlinear output feedback control of dynamically positioned ships using vectorial observer backstepping,” *IEEE Trans. on Control Systems Technology*, vol. 6, no. 1, pp. 121–128, Jan. 1998.
- [4] Y. Fang, E. Zergeroglu, M. S. de Queiroz, and D. M. Dawson, “Global output feedback control of dynamically positioned surface vessels: an adaptive control approach,” in *Proc. of the American Control Conf.*, Arlington, VA, June 2001, pp. 3109–3114.
- [5] K. D. Do, Z. P. Jiang, and J. Pan, “Underactuated ship global tracking under relaxed conditions,” *IEEE Trans. on Automatic Control*, vol. 47, no. 9, pp. 1529–1536, Sep. 2002.
- [6] M. R. Katebi, M. J. Grimble, and Y. Zhang, “ H_∞ robust control design for dynamic ship positioning,” *IEE Proc. - Control Theory and Applications*, vol. 144, no. 2, pp. 110–120, Mar. 1997.
- [7] P. Krishnamurthy, F. Khorrami, and S. Fujikawa, “A modeling framework for six degree-of-freedom control of unmanned sea surface vehicles,” in *Proc. of the IEEE Conf. on Decision and Control/European Control Conf.*, Seville, Spain, Dec. 2005, pp. 2676–2681.
- [8] P. Krishnamurthy, F. Khorrami, and T. L. Ng, “Control design for unmanned sea surface vehicles: hardware-in-the-loop simulator and experimental results,” in *Proc. of the 2007 International Conf. on Intelligent Robots and Systems*, San Diego, CA, Oct. 2007.
- [9] P. Krishnamurthy, F. Khorrami, and T. L. Ng, “Obstacle avoidance for unmanned sea surface vehicles: a hierarchical approach,” in *Proc. of the 2008 IFAC World Congress*, Seoul, Korea, July 2008.
- [10] E. Lefeber, K. Y. Petterson, and H. Nijmeijer, “Tracking control of an underactuated ship,” *IEEE Trans. on Control Systems Technology*, vol. 11, no. 1, pp. 52–61, Jan. 2003.
- [11] A. Loria, T. I. Fossen, and E. Panteley, “A separation principle for dynamic positioning of ships: theoretical and experimental results,” *IEEE Trans. on Control Systems Technology*, vol. 8, no. 2, pp. 332–343, Mar. 2000.
- [12] F. Mazenc, K. Pettersen, and H. Nijmeijer, “Global uniform asymptotic stabilization of an underactuated surface vessel,” *IEEE Trans. on Automatic Control*, vol. 47, no. 10, pp. 1759–1762, Oct. 2002.
- [13] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Saddle River, NJ: Prentice Hall, 2009.
- [14] P. E. Hart, N. J. Nilsson, and B. Raphael, “A formal basis for the heuristic determination of minimum cost paths,” *IEEE Trans. on Systems Science and Cybernetics*, vol. SSC-4, no. 2, pp. 100–107, July 1968.
- [15] P. Krishnamurthy and F. Khorrami, “GODZILA: A low-resource algorithm for path planning in unknown environments,” *Jour. of Intelligent and Robotic Systems*, vol. 48, no. 3, pp. 357–373, March 2007.
- [16] T. L. Ng, P. Krishnamurthy, F. Khorrami, and S. Fujikawa, “Autonomous flight control and hardware-in-the-loop simulator for a small helicopter,” in *Proc. of the IFAC World Congress*, Prague, Czech Republic, July 2005.